Credit-Induced Moral Hazard in Insurance: Theory and Evidence from Ghana∗+

Francis Annan
Columbia University

October 31, 2017

Abstract

Standard insurance contract requires upfront payments by consumers to protect against potential future losses. However, consumers in developing countries often buy insurance on credit. While this may allow consumers facing credit constraints to acquire more coverage, it might amplify moral hazard. I evaluate the effect of this moral hazard by exploiting an unexpected regulatory reform in Ghana that made it illegal to buy car insurance on credit; creating an exogenous variation in contract choice: the vast majority (99.5%) of consumers who used to buy comprehensive insurance on credit switch to buying legally-required but cheaper liability insurance with less than 1.6% dropping out of insurance after the reform. Prices are set by the government and cannot be adjusted by insurance companies in response to the reform. I formulate a model that allows for selection and moral hazard, and show that if contracts with higher coverage only increase claims, a simple difference estimator gives a lower bound on the effect of moral hazard. I combine this result with unique administrative data on contracts to document three additional sets of findings. First, there is evidence of moral hazard in the market which was averted by the regulatory reform. Second, moral hazard is responsible for the reduction in average size of claims and the number of claims by 46% and 22% respectively, leading to a 12% increase in insurance company profits. Finally, I show that abstracting from selection while learning about moral hazard over estimates its effect substantially. Back-of-the-envelope calculations assuming risk aversion and limited enforcement of credit arrangements suggest that the loss in consumer welfare attributable to the regulatory reform do not outweigh the gains in producer welfare. These results have wider applicability, both to interlinking credit with insurance markets and to the study of credit constraints.

1 Introduction

Consumers in developing countries often buy insurance on credit. These arrangements between insurers and consumers allow consumers to get coverage but defer premium payments to a later period. Such deferral is similar in principle to interlinking credit and insurance markets. The view that market inter-linkages act as mechanisms to overcome the problems of imperfect information, enforcement and to co-develop markets has long been emphasized.[1] In turn, this has led to a growing empirical research that bundles credit with insurance and vice versa, finding either increases or decreases in take-ups, respectively.

When credit is bundled with insurance, the effects on insurance demand have been unambiguously positive. For example, Liu et al. (2016) find that delaying premium payments for livestock mortality insurance increases the take-up of insurance in China; Casaburi and Willis (2017) find even larger increases in take-up rates for a crop insurance product in Kenya.[2] However, by bundling credit with insurance, particularly, it may increase demand but induce moral hazard in insurance, a trade-off that I study in this paper. This potentially negative effect of interlinking these two markets has been so far ignored in the literature.

This paper documents that insurance arrangements that defer some proportion of premium payments to the future increase insurance demand, and argues that such contractual arrangements can lead to substantial moral hazard. I evaluate an insurance policy experiment that made it impossible to buy car insurance on credit. Car insurance is crucial for businesses to develop, especially in developing countries where many people operate transport vehicles as small and medium enterprises.[3] It forms a large private market, but may fail

---

[1] Early works date back to Braverman and Stiglitz (1982, 1986) who show how a principal may interlock two contracts to induce more favorable outcomes. For example, a trader-lender may offer a farmer who borrows from him lower prices on inputs (seeds; fertilizers), since the probability of default is reduced when such inputs are used. Relatedly, Carter et al. (2013) show that interlinking credit and insurance contracts allow both markets to co-develop, as compared to when the markets are in isolation.

[2] When insurance is rather bundled with credit, the effects are mixed. Banerjee et al. (2014) find that by requiring loan clients to purchase health insurance at the time of renewing their loans, many (16 percentage points) borrower clients dropped out of borrowing in India; Karlan et al. (2014) rather find significant increases in the take-up for credit in Ghana.

[3] The employment-gains from car insurance may also be exemplified by a recent innovation in the car business sector, called "work n pay". Slightly different from sharecropping, work n pay are contractual arrangements that allow commercial drivers and the young to acquire cars and work with it, while making payments for the car within a period of time—typically two and half years. The arrangements are such that the drivers make part payment of the cars and work to pay the rest in installments. Private conversations with work n pay drivers in Ghana suggest that (i) common challenges to this business are accidents and robbery,

to function and grow due to frictions like moral hazard and other inefficiencies.[4] The reform allows me to see the change in contract choice that follows the end of the credit market and associated claims. This allows me to characterize how the access to credit in the previous regulatory framework induced moral hazard.

The regulatory reform I study was unexpectedly imposed by the National Insurance Commission (NIC) of Ghana. The reform is called "no premium, no cover" and requires insurance firms to collect premiums upfront before providing insurance coverage. Prior to the change, insurers were allowing customers to purchase insurance coverage on interest-free credit and to pay later; so the reform made lower coverage more attractive.

To learn about moral hazard, I formulate a model that allows for selection and moral hazard and derive bounds on moral hazard. This formulation recognizes the complex interplay between multidimensional selection and moral hazard in insurance. With selection, individuals are heterogeneous in their unobservable attributes such as risk type and risk aversion; and thus self-select into different kinds of contracts. The bounds are based on restrictions that stem from agency theory and exogenous variation in contract choices induced by the policy reform. Following the seminal work of Holmstrom (1979), most of the contracts and moral hazard literature have assumed the Monotone Likelihood Ratio Property (MLRP), which requires that better outcomes are likely due to higher effort. I combine the MLRP with two other conditions. The first is that the actual timing of the reform is uncorrelated with individuals' unobserved heterogeneity; the second is that customers who select higher coverage contracts will not supply more effort. In the spirit of Manski (1990), these conditions allow me to derive bounds on moral hazard. I show that a simple difference estimator yields a lower bound on the effect of moral hazard. The economic model and restrictions

---

but (ii) the availability and provision of insurance for the cars largely influence their decisions to sign up for such arrangements. Even, major insurance companies (and the government) have recently taken up the initiative to offer work n pay schemes under soft re-payment terms with full insurance coverage. See https://www.ghanaweb.com/GhanaHomePage/business/200-new-vehicles-for-Youth-in-Driving-265953

[4]A vast theory shows that frictions from information asymmetries (traditionally, moral hazard and adverse selection) limit the ability of formal insurance and credit markets to function (Rothschild and Stiglitz 1976; Ghosh, Mookherjee and Ray 2000). This has led to a careful empirical research seeking to learn and overcome the various informational asymmetries like moral hazard, but with a substantial focus on developed country contexts. Thus, little is known about the relative significance of moral hazard in developing countries, a gap I will fill in this paper.

provide micro-foundations for the econometric model and empirical exercise.

I leverage a rich set of customer level insurance and credit records that span 2013–2015 and come from the administrative files of the largest branch of the largest General Business insurance company in Ghana. Two unique features about the data are notable: (i) it spans a period before and after the reform whereby it became impossible to buy insurance on credit; and (ii) it allows for tracking customers across contract years. In doing so, I observe who used to buy insurance on credit, and who switched either from higher to lower coverage. The use of administrative data sets on insurance contracts is common for research in developed countries, but in developing countries, such data have historically been unavailable for research. The combination of rich customer level administrative data and quasi-experimental variation from an insurance policy reform enables me to evaluate moral hazard's effect and the possible linkages with credit constraints in a developing country setting.

I start by asking how the introduction of the reform impacted customers' choice of insurance coverage. There are two choices in the contracts menu: basic, which is legally required and provides only third party protection, and comprehensive/higher coverage, which insures against all responsible liability. I find that the policy reform led to a 6 percentage points drop in the share of comprehensive contracts. I also show evidence that consumers who bought comprehensive contracts were more likely to buy on credit than those who only bought basic coverage, and switched to lower contracts after the reform removed the possibility of buying insurance on credit. The overwhelming majority (99.5%) of consumers who used to buy comprehensive insurance on credit switch to cheaper basic-liability insurance, with less than 1.6% dropping out of insurance altogether after the reform

I then exploit the plausible assumption that the actual timing of the policy reform is uncorrelated with individuals' unobserved heterogeneity to construct a simple and general test of the presence of moral hazard. The idea behind the test is that: under the null of no-moral hazard, a change in insurance coverage induced by the reform and not selection should not cause a change in outcomes, either claim amounts or occurrence of loss. This

follows from Escanciano, Salanié and Yildiz (2016), who show that exogenous variation in contract menus allows for a test of moral hazard under selection. Both graphical and formal tests suggest the existence of moral hazard in this market. This existence test, although simple and clean, only provides inference about whether or not moral hazard is absent; it is unable to evaluate the effect of moral hazard.

I proceed to investigate moral hazard and its effect using the bounds. Consistent with the results of the first test, I find strong and convincing evidence of moral hazard. The evidence is robust across various definitions of insurance outcomes. Moral hazard induced significant leakages in insurance claims. The empirical results suggest a lower bound moral hazard estimate of (i) GHC52 (USD18) which translates to 46% of average size of claims; and (ii) 22% of the number of claims between two contract years. These moral hazard effects, averted by the policy reform, correspond to a 12% increase in average firm profits for the company's auto-business line.[5] Beside the increase in firm profits through reduction in moral hazard, the switch to contracts with lower coverage due to the policy reform may lead to loss in consumer welfare. Under various assumptions about risk aversion, enforcement and repayment of premium debts, I conduct back-of-the-calculations of the welfare loss and gains from making it impossible to buy insurance on credit. I find that the loss in consumer welfare is about 11% of the gain in producer welfare; suggesting that the regulatory reform is not welfare-decreasing, overall.

There are at least two potential channels through which the reform may have shifted choices of insurance contracts and thus moral hazard: binding credit constraints, and changes in relative prices. The analysis established that the results are likely driven by credit constraints. In particular, moral hazard is much larger for the group of consumers who tend to buy insurance on credit. However, the decision to buy insurance on credit could

---

[5]The estimated total cost of moral hazard, averted by the regulatory reform, is about GHC52,703,889 (USD17,567,963) for the insurance industry. Expected revenues and costs associated with providing insurance are simply derived using realized premiums and indemnities from the insurer's policies data, respectively. This calculation allows for an insurance loading of 25% (reflecting the administrative costs of processing claims) but ignores any direct returns on company investments of collected insurance premiums.

either be because the consumers are actually credit-constrained, or financially "savvy" with no intentions to re-pay their premium debts. I find as high as 79% repayment rates for premium debts, which is inconsistent with the latter. Why repay debts before the expiration of insurance contracts, if the goal is to take advantage of the credit provision? In contrast, the evidence is consistent with credit constraints: consumers who switched to contracts with lower coverage after the regulation were those who bought contracts with higher coverage earlier and with credit. Next, if insurance firms were to adjust premiums in response to the policy reform then it will be unclear whether or not the moral hazard results are also driven by changes in relative prices. I find evidence against such alternative channels. This paper thus documents the possible effect of credit constraints on moral hazard, in particular in the context of a developing country.

This paper contributes to several strands of literature. First, it contributes to the literature that examines the importance of inter-linked markets in developing countries.[6] This line of research have appealed to the use of inter-linkages to overcome the inefficiencies from incomplete markets (Braverman and Stiglitz 1982, 1986), along with the development of the various markets (Carter et al. 2013). Many experimental studies have bundled insurance with credit, finding either increases or decreases in the demand for credit (Gine and Yang 2009; Banerjee et al. 2014; Karlan et al. 2014). Others—experimental and quasi-experimental— have bundled credit with insurance, finding significant increases in the take-up of insurance (Liu et al. 2016; Casaburi and Willis 2017). This paper documents the moral hazard consequences of bundling credit with insurance, suggesting the difficulty of developing both markets.

Second, this paper adds to the growing empirical literature on testing for the existence of asymmetric information in both private and social insurance markets (Chiappori and Salanié 2000; Finkelstein and Poterba 2002; Krueger and Meyer 2002; Cohen and Dehejia 2004; Cohen and Einav 2007; Einav, Finkelstein and Levin 2010; Einav et al. 2013; Hendren

---

[6]Bardhan (1980), Bell (1988), and Bardhan (1989) provide authoritative surveys about market inter-linkages.

2013; Hansman 2016; Kim 2017 and many others). Major parts of this literature have focused on (i) insurance markets in developed economies; less so for developing country settings, and (ii) testing the existence of asymmetric information in general by exploiting correlations between insurance purchases and claims; mostly in the spirit of the "positive correlation" tests of Chiappori and Salanié (2000) and Chiappori et al. (2006). This paper contributes by separating moral hazard from selection, as well as estimating its effect[7] in a developing country. The simple way to think about moral hazard's effect is the loss in average profits to insurers or in parts of social value due to its presence. Estimated quantities can be informative in thinking about how to quantify the welfare implications of moral hazard and potential public policy interventions.

Methodologically, this paper differs from the above literature. I develop and use a bounds approach to detect moral hazard, where unobserved heterogeneity or adverse selection is allowed to impact the response function in an unrestricted manner. The unobserved heterogeneity is allowed to be a vector of hidden information without any restriction on the dimension.[8]

There are papers that focus on one informational friction such as adverse selection by abstracting from the other (e.g., Cohen and Einav 2007). The proposed approach allows me to evaluate the implication of this. Suppose I assume away selection, then I find huge moral hazard effects which are larger than the credible estimates in subtantial magnitudes: 4-7 times larger. This exercise documents that abstracting from one dimension can have large and nontrivial consequences. Taken together, the proposed approach provides an alternative

---

[7]One recent exception to estimating moral hazard's effect is Schneider (2010), who provides a conservative estimate of moral hazard (about 16%) increase in the accident rate for drivers who own versus lease their taxicabs in New York City. Unlike in Schneider (2010), the empirical approach here is nonparametric and focuses on both loss occurrence and claim outcomes. I take advantage of these two outcomes to investigate whether moral hazard is due to occurrence of losses or a shift in the distribution of claims, respectively. Relatedly, Gerfin and Schellhorn (2006) used deductibles as an excluded instrument and statistical restrictions to bound moral hazard. Their outcome variable was the probability of a doctor visit in Switzerland. But unlike in Gerfin and Schellhorn (2016), I combine microfounded restrictions with an exclusion from a policy reform restricting the sale of insurance on credit which permits potential linkages between moral hazard and credit constraints, akin to low-income environments. To put the results into context: this paper provides moral hazard estimates that are 1.5-3.0 times larger than estimates from developed countries.

[8]A policyholder may be characterized by multi-dimensional selection attributes including risk types and risk preferences, and empirical work has shown evidence from different contexts (Finkelstein and McGarry 2006 in long-term care insurance; Cohen and Einav 2007 in car insurance; Davidoff and Welke 2007 in reverse mortgage; Fang, Keane and Silverman 2008 in Medigap health insurance). Yet, an identifying framework that accounts for these adverse selection attributes in an unrestricted manner is still lacking.

benchmark to evaluate the effect of moral hazard, and can be applied to study moral hazard in other insurance and financial market contexts.

Finally, this paper is related to the broader literature that studies the economic importance of credit constraints. Our knowledge about credit constraints is important for the optimal design of private and public programs, as they tend to alter the potential behavioral response to these programs. In developing countries, many papers have shown that liquidity constrains the demand for agricultural insurance (Cole et al. 2013; Karlan et al. 2014), health products like anti-malaria bed nets (Cohen and Dupas 2010), and induce motives for precautionary saving (Lee and Sawada 2010). In developed countries, liquidity constraints have been shown to limit investment in human capital (Dynarski 2003), cause significant response to unemployment insurance durations (Chetty 2008), and consumer bankruptcy decisions (Gross, Notowidigdo and Wang 2014). Since the moral hazard results are explained by credit constraints, this paper establishes a possible link between the two strands of literature on credit constraints in developing countries and market failures through incentive effects, particularly the private insurance sector. In particular, while reducing credit constraints may be good, I document a situation where such a reduction may lead to inefficiency.

The remainder of this paper is organized as follows. Section 2 provides background on the setting and policy reform. Section 3 builds an economic model to highlight the complex interplay between selection and moral hazard. Section 4 discusses the data and research design; 5 presents a test and results for moral hazard based on the research design and formulation in section 3. Section 6 lays out the bounds analysis and presents the bounding results on moral hazard. The possible explanations, caveats and implications are discussed in section 7. Section 8 concludes with applications, extensions and policy dimensions. Details and some proofs are in the Appendix.

2   Setting and policy experiment

I discuss the details of the institutional setting, policy reform and reasons underlying the motives of insurance firms in lending premiums in this section. I had extensive personal conversations with insurance companies. The findings which are largely consistent with the empirical evidence are presented to motivate the research approach.

2.1   The legal environment

Automobile insurance is compulsory in Ghana, as in other countries.[9] By this, all individuals operating a car are legally required to purchase insurance. This is usually for two principal reasons. First, compulsory insurance ensures that some compensation is provided for those who are injured in automobile accidents. Second, it forces drivers to internalize part of the externality imposed on others by their driving, especially in the case where drivers have bounded assets (Cohen and Dehejia 2004).[10]

In Ghana, the specific types of auto insurance contracts can range from "third-party" liability to "comprehensive" coverage. The minimum requirement by law is the third-party which provides protection to others when accidents occur. Comprehensive contracts on the other arm provide coverage for all responsible claims. Enforcement of the compulsory insurance law embody two dimensions: automobile drivers are required to report their insurance status at time of accident, and penalties can range from large fines to jail terms when the driver is unable to show proof of coverage. Even so, enforcement can be limited. For instance, it is estimated that about 20-36% of cars in Ghana are uninsured.[11]

---

[9]Compulsory insurance regulation was first introduced in Ghana in 1958. The Motor Vehicles (Third Party Insurance) Act 1958, ACT 42 makes it illegal to drive a motor vehicle on public roads without insurance covering third-party liabilities, at minimum.

[10]In low-income and developing country contexts, individuals likely have limited assets. This may provide more justification for compulsory automobile insurance laws in such contexts.

[11]Data about uninsured cars are, of course, not available. I estimate the fraction of uninsured using the following back-of-envelope exercises. For 2012: The National Insurance Commission (NIC) of Ghana issued 759,691 stickers to identify cars that have legitimate insurance cover. But the Driver and Vehicle Licencing Authority (DVLA) reported that 946,284 vehicles were inspected for roadworthiness. This means that about 186,593 vehicles on the roads did not have insurance cover; suggesting a 19.72% uninsured rate. See https://www.ghanaweb.com/GhanaHomePage/business/200-000-cars-without-insurance-270312 For 2014, I estimate that about 36% of all registered cars are uninsured: I collected data from the National Road Safety Commission (NRSC) about total number of registered cars (1885836). I then estimated the total number of insured cars in Ghana (~1190476). I estimate this by dividing the number of insurance policies at the end of my sample (~30,000) by the

2.2 The market, regulation and why it was introduced: in brief

The insurance industry in Ghana has undergone many periodic modifications through the passage of various acts and reforms. The industry in its current state is largely governed by Insurance Act 2006, ACT 724. Act 724 is a national act and complies with the Core Principles of International Association of Insurance Supervisors (IAIS) as well as provides regulatory powers to the National Insurance Commission (NIC 2011; NIC 2015). ACT 724 made the insurance industry a more regulated one, where the NIC is granted powers to regulate and control the business of insurance markets in Ghana. A significant feature of this market, particularly for car insurance contracts, is that the NIC regulates and effectively sets the premiums for policies by providing a uniform price formula to all insurance firms.

On April 1 2014, the NIC introduced a reform called "no premium, no cover". Figure A4 in the Appendix shows the timeline of the policy. The regulators agreed on the policy on October 12, 2013, and then announced and implemented it on April 1, 2014—resulting in an implementation lag of seven (7) months. This policy reform requires all insurance firms to collect premiums upfront before providing insurance coverage. People were able to buy coverage on credit and pay later before the reform began. So, the reform marked the end of the credit market and directly implies that insurance companies will no longer be able to sell insurance products on credit to customers. The sale of insurance on credit created an accounting problem: premium payments were delayed leading to a mismatch in the actual re-payment times and the preparation of balance sheets. All unpaid premiums at the time of preparing financial statements are declared outstanding. This made it difficult for insurance companies to pay their reinsurance premiums on time since most premiums remained outstanding. In turn, the reinsurers were unable to pay their retrocessionaires on time; exposing the entire industry to substantial liquidity risk.

product of the share of the market for the company that provided the data (21%) and the best guess of the share of policies from the company's headquarters branch (12%) where the contracts data came from. Finally, I divided the difference between the total number of insured cars and the total number of registered cars by the total number of registered cars; yielding about 36.01% uninsured rate.

2.3 Pre-policy regime: stylized facts

Before the introduction of the reform, insurers were essentially serving a dual role: loss-risk takers and premium-lenders. Enforcement of lending or credit arrangements is based on the direct repeated interactions between the insurers and consumers. In addition, insurers use market intermediaries (i.e., insurance brokers and agents) to enforce credit arrangements as many insurance contracts are acquired through the intermediary channels. As shown in Figure 1, about 53 percent of all contracts sold prior to the reform were through intermediaries. Intermediaries have a better motivation to collect premium debts, as most insurance companies would not pay all commissions[12] due them unless the premiums are paid.

[Figure 1 about here.]

From the consumers side, they were able to enjoy flexible payment terms by deferring the payment for their policies to a later date. In instances where there is a loss while the premium is still outstanding, consumers are required to settle the premium arrears in full before the loss is paid. In other instances, however, the premium outstanding is deducted to the loss payment before payment to the policy holder. In part, this uncertainty combined with the crucial role of trust in insurance transactions explains why only 27 percent of consumers acquired insurance on credit prior to the regulatory reform. Figures 2a and 2b show the take-up of credit to buy insurance over time prior to the regulation. Both figures are based on a probit regression of whether or not a customer purchased insurance on credit. Figure 2a includes only monthly dummies as regressors, whiles Figure 2b adds a linear control for time trend and customer characteristics. As shown, 27% of consumers purchased insurance on credit. In addition, the take-up of insurance on credit is stable across the various months before the policy's implementation. This suggests that the implementation of the no-credit policy was unexpected by consumers.[13]

---

[12]The commissions averaged about 5% per unit premium.

[13]It is reassuring that consumers did not anticipate the actual implementation or announcement of the regulation. This is useful in Section 4, where I argue that the actual timing of the policy is exogenous and uncorrelated with unobserved consumer attributes.

[Figure 2 about here.]

From the side of insurers, it was common for firms to report outstanding premiums on their annual financial statements. Figures 3(a) and 3(b) show the distribution of premiums in debt prior to the regulation. The figures reflect the amount of premium (GHC) and its percentage as a share of actual premiums at the time contracts are signed, respectively. For customers who bought insurance on credit, there is evidence of substantial premium debts, ranging between 0.2-100% of premiums. Together, the total debt represents 64.2% of actual premiums for consumers who took insurance on credit. Expressed as a share of all premiums for the auto-business line, this is about 33.3%.

[Figure 3 about here.]

Given that many insurance contracts were sold through market intermediaries, I superimpose the distribution of premiums in debt across the two sources of selling insurance policies in Figure 4. There is evidence that consumers are more likely to initiate contracts on credit through the intermediary channels.

[Figure 4 about here.]

Finally, as discussed earlier, enforcement of credit arrangements relies on direct repeated interactions and the use of market intermediaries. I assess this in Figures 5(a) and 5(b) showing the repayment rate of outstanding premiums. Extensively, Figure 5(a) indicates that 21.3% (out of 27.0%) of customers who purchased insurance on credit repaid their premium debts before their contracts expired; translating to a repayment rate of about 79.0%. The repayment rate is not significantly different if I look at the actual amount of premiums in debt. Intensively, Figure 5(b) shows that about 24.4% (out of 33.3%) of the total premium debts were repaid prior to the no-credit policy. This implies a repayment rate of about 73.2%. Both results point to a high repayment rate of outstanding premiums prior to the policy's implementation; suggesting a low credit risk/delinquency for allowing consumers to buy insurance on credit.

[Figure 5 about here.]

2.3.1 Why were companies willing to accept credit payments before the reform

It is surprising that the insurance firms were lending premiums. What is especially striking is that they were accepting credit payments at interest-free rates. I summarize the two principal reasons below.[14]

Competition under regulated-prices As discussed earlier, the NIC effectively sets the premiums. So, the insurance firms were essentially selling the regulated-price contracts, with no room to directly influence how their prices are set. Thus, giving credit was considered a way to indirectly influence or reduce prices to maintain their market share. The zero-interest rate can be understood formally in a simple model of two competing firms who take premium as given, and then compete over credit. Applying Bertrand strategies, I find that zero (negative) interest rate is a possible equilibrium outcome. An illustration is provided in the Appendix.

Application of accounting standards and reserve requirements Operating within accounting frameworks, it is assumed that once someone owes the insurance company, it is an asset. The outstanding premiums actually make the companies' accounts look more attractive on the surface, regardless of the opportunity costs: forgone investments. For companies to formally operate, they are required to meet certain capital and reserve requirements set by regulators. So, providing coverage on credit was considered a good strategy to circumvent such reserve requirements. Furthermore, most of the outstanding premiums were eventually recovered later. As a result, selling insurance on credit was deemed less risky (i.e., low credit risk).

2.4 Post-policy regime: stylized facts

The policy mandate disallowed the purchase of insurance on credit: consumers cannot defer

---

[14]Several possible reasons are discussed, but the first two presented here are the principal explanations; the rest are relegated to the Appendix. These discussions yield testable implications that future work will aim to explore.

or owe any portion of their premiums. In addition, firms were required to write off all premium debts from their books.

The reform is strictly enforced. Since its introduction, the NIC undertakes occasional unannounced visits to audit insurance company records. The penalty of noncompliance is as high as ten (10) times the amounts in outstanding debts; forcing the insurance companies to comply with the reform's requirements. The no-credit reform system ultimately helped to cut down the rising outstanding premium profiles of insurance companies. At the same time, it ensured that the companies have enough capacity to honor their reinsurance obligations. There were two additional effects: (i) policyholders who could afford full payment but were taking advantage of the credit-based system had to pay in full; and (ii) those who were credit constrained and could not afford higher coverage had to cut down coverage, subsequently. I discuss these two effects as candidate mechanisms underlying the results.[15]

Finally, most countries in the west-African sub region have been encouraged to embrace similar market policy reforms. For instance, Nigeria and Gambia have followed with similar no-credit regulations in 2014 and 2015, respectively. These regulations have been projected to have positive implications for the balance sheets of underwriting companies and the overall financial health of the insurance industry.

2.5 Private conversations with company

To better understand the impact of the reform[16], I had private conversations with staff and managers of the insurance company that provided the data. Some extracts from the personal conversations follow

---

[15]Section 2.3 suggests a low credit risk due to the higher repayment rates of premium debts, 79%. This will seem imply that the latter effect (credit-constraint) dominates. I explore this in more detail in Section 7.

[16]All insurance products, excluding life insurance are broadly classified in the industry as General Business. The analysis utilize a rich set of individual level auto-insurance records (spanning 2013-2015) that come from the administrative files of the largest General Business insurance company in Ghana (about 21% of the entire market in 2014; the data description is contained in Section 4). The company offers different insurance products through their business lines e.g., automobile, workman compensation, bonds, marine, and etc. In this paper, I focus on the automobile insurance line which accounted for 55.4% of their net premium holdings. In addition to the simple nature of auto-contracts, automobiles pose environmental consequences that will be studied later as an extension to this paper.

"The April 2014 reform triggered some important changes. Particularly, it made insurance unaffordable to clients in that most folks dropped from more generous [Comprehensive] to basic [Third party] plans."

February 2015

"Some of our clients switched from Comprehensive to Third Party plans because the reform made the insurance purchasing rule more stringent."

February 2015

The quotes resonate with economic intuition as the reform imposed additional liquidity-cost on the purchase of insurance. There are potential income effects from constraints in liquidity which affects insurance purchase as a normal good. Figure 6 provides supportive evidence from the insurer's data

[Figure 6 about here.]

This figure is based on a simple frequency estimator. First, the figure demonstrates that the market share of comprehensive cover is significantly lower due to the introduction of the reform. Second, the drop in probability of the purchase of comprehensive contract is substantial, about 6 percentage points. It is useful to note that most of the comprehensive policyholders credit prior to the reform, and so were directly affected by the reform. This can be seen from the transition matrix displayed in Table 1. In particular, over 99.4% of consumers who purchased insurance on credit (27%) switched from comprehensive to basic contracts after the no-credit regulation. Most notably, customers who acquired comprehensive contracts were much more likely to do so on credit, compared to customers who bought minimal coverage. The reform provides plausibly exogenous variation in customers' choice of contracts: basic versus comprehensive insurance. The background of this research's design is based on the major policy change, in which it is used as an instrument for contract choices.

[Table 1 about here.]

In the next section, I present a simple economic model that illustrates a selection problem

confronting the analysis of moral hazard–as this paper aims to learn about moral hazard and its linkages with liquidity via the policy reform.

3   Mixed economic model and effects

I consider a typical insurance market set-up where consumers have asymmetric information, which allows for adverse selection and moral hazard. Two economic actors enter into a contract: the principal, or the insurer and the consumer, or the insuree. Multiple contracts may be offered. Throughout, I black box the principal's role and focus on the consumer. A key feature of the set-up is that consumer's private information matters to the principal but it is unobserved to the principal.

3.1   Background model

Index a consumer by i and consider a population of insurance customers whose observed characteristics are denoted by X_i. The observed characteristics of customers are assumed to be exogenous. I will ignore conditioning on X_i for convenience.

Technology & Contract Formally, the consumer i owns the following production technology

$$Y_i = g(e_i, \alpha_i^y, \varepsilon_i)$$

where Y_i represents the insurance outcome. ε_i is a random variable that may capture random circumstances in the production technology, e.g. weather. e_i denotes the customer's choice of effort, capturing the prevention of accidents or limiting their severity. α_i^y captures hidden information that enters the customer's productivity. The principal observes the outcome Y_i but not the customer's effort e_i or random variable ε_i. The consumer chooses his e_i before the realization of the ε_i occurs. I will sometime refer to $g(.)$ as the structural response function.

Index a contract type by d. Then, I define an insurance contract as $C_d = \{\Pi_d, I_d(L)\}$. This pair specifies the insurance premium $\Pi_d \geq 0$ and indemnity $I_d(L) \geq 0$ for some loss

size L. Let D_i denote the customer's choice of contract. I shall restrict attention to binary contracts $D_i \in \{d : 0, 1\}$, to be consistent with the empirical setting where consumers choose either basic or comprehensive contract cover, respectively. In this case, Π_0 denotes the premium for basic contract and Π_1 corresponds to that for comprehensive contract.

Timing & Model Let α_i^u be hidden information that enters the customer's utility function u, capturing preferences and risk aversion; and define $\alpha_i = (\alpha_i^y, \alpha_i^u)$. The vector α_i can be thought of as customer's unobserved heterogeneity. To derive the model that guides the subsequent analysis, consider the following sequence of customer's moves. First, the consumer i privately observes his type α_i. Second, conditional on his type, the consumer makes a contract choice over $D_i = 0, 1$. Third, suppose that the consumer chooses D_i. Then conditional on (D_i, α_i), effort levels are respectively chosen as[17]

$$D_i = 0 : \max_{e_i} \left(\mathbb{E}_{\varepsilon} u[R(Y_i, \Pi_0, I_0)] | e_i, \alpha_i - e_i \right)$$
$$D_i = 1 : \max_{e_i} \left(\mathbb{E}_{\varepsilon} u[R(Y_i, \Pi_1, I_1)] | e_i, \alpha_i - e_i \right)$$

where $u[]$ is a von Neumann-Morgenstern utility function that satisfies standard conditions. $R(Y_i, \Pi_d, I_d)$ denotes the net income flow from buying insurance and expectations are taken over the random shocks ε.[18] Here, the consumer will optimally choose his level of effort to maximize his expected utility less his disutility from effort. Effort e_i has been normalized so that one unit of effort translates into one unit of disutility in expectation.

Putting all the pieces above together, $e_i = e_i^*(D_i, \alpha_i^y, \alpha_i^u)$ solves

$$\max_{e_i} \left(\mathbb{E}_{\varepsilon} u[R(Y_i, \Pi_d, I_d)] | e_i, \alpha_i - e_i \right)$$

---

[17](i) A summary of the model's timing is provided in Figure A1 in the Appendix. (ii) There is a uniform menu of contracts across all firms in the empirical environment so direct competition (e.g., via price; product), which could permit consumers to strategically seek for "better" priced-contracts across firms, is of little concern. The insurance market is highly regulated and controlled by the government, as discussed in Section 2. The model set up is a recursive problem, where in principle the customer will also choose the contract $D_i = 1$ if and only if its net flow utility is the highest among the other feasible candidate contracts.

[18]Note the difference between α_i^y and ε_i: α_i^y are all productivity shocks available to the consumer before contracts are established (e.g., pre–contract weather realizations), but ε_i does not come in until efforts are made and thus beyond the customer's control (e.g., post–contract weather realizations).

This implies that $D_i = \sigma(\alpha_i)$ and $e_i = e_i^*(D_i, \alpha_i)$. Together, the implied model can be cast as a triangular system

$$Y_i = g(e_i^*(D_i, \alpha_i), \alpha_i^y, \varepsilon_i)$$
$$D_i = \sigma(\alpha_i)$$

Discussions The model formally shows how e_i maps into D_i and $\alpha_i = (\alpha_i^y, \alpha_i^u)$. First, note that consumer i's contract choice is not randomly assigned. This crucially depends on his type, as illustrated above; hence the observed random variable D_i is potentially endogenous. The endogeneity of D_i may also arise through the correlation of the unobservables $(\alpha_i, \varepsilon_i)$. In this mixed model, it is difficult to learn about moral hazard alone because the choice of contracts that will create incentives for effort choices are also determined by unobserved heterogeneity or some exogenous, third factor.[19] One possible solution would be to assume that unobserved heterogeneity α_i, which structurally leads to nonrandom sample selection, is some additive term in a model that is linear in outcomes and contract choice, and then use fixed effects to control for this. But clearly controlling for fixed effects by differencing out additive α_i terms may be inadequate.

I explore the idea of instrument exclusion from a regulatory change to learn about moral hazard, in which the change exogenously modify the contract choice and incentives. The following discusses the regulatory change approach and how it is used to quantify the effect of moral hazard.

3.2 Effects and definitions

To cast the problem using counterfactual notation as in the treatment effects literature, that is, the outcome that would have been observed if the consumer i with unobservables α_i and ε_i had been assigned the contract d, I fix d. This means that the customer's level of effort

---

[19]A naive test for moral hazard in the mixed model will either directly exploit the correlations between the customer's outcome Y_i and contract choice D_i, or between the outcome Y_i and the level of effort $e_i^*(.,.)$. But unfortunately, neither of these two approaches yields reliable inference since the correlations may be due to adverse selection α_i.

can be written as $e_i^*(d, \alpha_i)$. The corresponding production technology is

$$Y_i(d) = g(e_i^*(d, \alpha_i), \alpha_i^y, \varepsilon_i)$$

One needs an instrument Z, which is uncorrelated with unobserved heterogeneity; with $D_i = \sigma(\alpha_i, Z)$ to exogenously shift the $\sigma(., .)$ function. In the empirical analysis, Y_i represents insurance claims or loss occurrence and the instrument Z represents policy changes that exogenously induce changes in choice of insurance contracts. $D_i = 0$ corresponds to compulsory or basic contracts. These are mandatory contracts that drivers are required to purchase by law. Under this contract, only third party protection is provided for responsible claims. $D_i = 1$ corresponds to comprehensive contracts, where protection is provided for *all* responsible claims. Thus, comprehensive contracts may provide higher incentives for undesirable outcomes, as compared to basic contracts.

Moral hazard defined Following Escanciano et al. (2016) and Salanié (2005 Ch. 5), I define moral hazard as the causal impact of contracts. This embodies all non-contractible actions that affect the occurrence and distribution of losses or claim outcomes due to the terms of the contract. Specific examples include costly parking at safer places, wearing a seatbelt, and other negligence–be it strategic or mechanical. With this definition, two potential sources of moral hazard are possible: "ex-ante" moral hazard which occurs through changes in unobserved preventive efforts and "ex-post" moral hazard that arises when customers under-report claims by withholding claim or loss information strategically (Cohen and Einav 2007).

Formally, suppose there is no moral hazard, then it must be that $Y_i(d) \stackrel{dis}{\approx} Y_i(d')|Z_i$ $\forall d \neq d'$ where $\stackrel{dis}{\approx}$ is the shorthand notation for "has the same distribution as". Suppose there is moral hazard, then $Y_i(d)|Z_i$ should increase with coverage (d), where d corresponds to a contract choice. In this case, $Y_i(d)|Z_i$ increasing in coverage implies that worse outcomes are exogenously realized under higher coverage. I observe an IID sequence of observations $\{(Y_i, D_i, Z_i)_i : \ i = 1, ..., I\}$. Identifying moral hazard in the mixed model is equivalent to

examining changes in the joint distribution of $(Y, D)|Z$. The focus will be on

$$\mathbb{E}[(Y, D)|Z]$$

I drop the subscript i for easy illustration. The key point is that there exists a causal chain where Z exogenously shifts the distribution of $\sigma(.)$ (i.e. equivalently $\mathbb{E}[D|Z]$) which will in turn shift the distribution of Y via $e^*(.,.)$. More generally, I define the average structural function ASF (Blundell and Powell 2003) as

$$\mu_z(d) = \mathbb{E}[Y_i(d)|Z = z] \equiv \int g(e_i^*(d, \alpha_i; z), \alpha_i^y, \varepsilon_i) dF(\alpha_i, \varepsilon_i), d = 0, 1$$

where $F(.)$ represents joint distribution of the unobservables α_i and ε_i. Next, I can define the average treatment effect ATE of $D_i = 1$ versus $D_i = 0$ to be

$$\Delta = \mu_z(1) - \mu_z(0) > 0, \text{MH}$$

Δ essentially quantifies the average effect of exogenously shifting all consumers from the treatment status $D_i = 0$ to $D_i = 1$. As indicated above, $\Delta > 0$ is required for moral hazard. The presence of moral hazard leads to worse outcomes, which is measured by the size of $\triangle$; I call this moral hazard effect (MHE). I derive bounds for the three objects $\mu_z(1)$, $\mu_z(0)$ and Δ. The approach utilizes a model that is nonseparable in unobservables $(\alpha_i, \varepsilon_i)$ along with a plausibly random and exogenous policy instrument to eliminate contaminations that may be due to adverse selection.

4   Data, measurements and research design

This section describes the data and main research design of the paper, which requires the distribution of unobserved heterogeneity to be similar before and after the reform. I carry out several checks showing the validity of the policy instrument and research design.

4.1 Data

As mentioned in Section 2, I combine data from two major sources: administrative data and surveys.[20] The surveys embody private conversations with drivers and staff from the insurance company that provided the administrative data. From the administrative data, I observe the complete contract profile for each policy holder i in the insurer's files across two contract years t (2013/14 and 2014/15). Notable features about the data is that it spans a period before and after the policy reform and allows me to track customers over time. I define the following set of variables based on information from the data.

Treatment: $D_{it} = \mathbf{1}\left[Comprehensive\right]$ is an indicator for the choice of insurance contract, where basic contracts correspond to $D_{it} = 0$ and comprehensive contracts correspond to $D_{it} = 1$. The definition is guided by the nature of the Ghanaian automobile insurance market where consumers choose from the contract menu: basic versus comprehensive. As discussed in Section 3.2, basic contracts cover damages only for others, whiles comprehensive contracts cover all responsible claims when accidents occur.

Policy Instrument: $Z_{it} = \mathbf{1}\left[\tau_t > \bar{\tau}\right]$ equal to 1 for the contract period τ_t after major National reform $\bar{\tau}$. This construction follows because the introduction of the policy reform created an exogenous variation that induced changes in consumers' choice of insurance contracts. Since I exploit an instrument which comes from the reform changes before and after $\bar{\tau}$=April 1 2014, the identifying variation is essentially from a pre- and post-design, although different customers particularly those who bought comprehensive contracts were largely affected by the policy change; yielding an analog of difference-in-differences.

Policy instrument's relevance Figure 6 documents relevance of the policy instrument. It demonstrates that contract choices changed dramatically following the reform. Although skipped here, it is straightforward to formally test for relevance under the hypothesis that the reform does not affect insurance choice.

---

[20]Additional data about industry aggregates are obtained from the annual reports of insurance companies and the NIC. Traffic information about overall accident rates and registered vehicles are also obtained from Ghana's National Road Safety Commission of the Ministry of Transportation. http://www.nrsc.gov.gh/

Outcome: Y_{it} denotes either claim amount or loss occurrence that is realized by customer i at time t. These are the two main outcomes of interest. The claim outcome is defined as the per period insurance claim received by a policyholder. There are two contract years spanning the days between April 1, 2013 - March 31, 2015. Claims (or loss occurrence) cannot be less than zero so I treat all negative outcomes in the data set ($<0.001\%$ of sample) as missing at random, as these are likely errors.[21]

Controls: It is important to condition on all publicly observed customer characteristics (Chiappori and Salanié 2014) that either determine or do not determine insurance prices. The data set includes a rich set of individual level information from the insurance company. These include the following variables:

(I) Level of no-claim-discount NCD: This measures the amount of premium discount that the policyholder receives from the company. In practice, customers receive a discount in period t for a no loss record in $t-1$. The discounts are adjusted accordingly once the customer gets an auto accident that triggers an insurance payout. To prevent under-reporting of claims, discount amounts are typically less than claims amounts.[22] While I do not have enough data to explicitly model dynamics, I believe the NCD variable possibly captures how customers respond to losses and discount across different contract periods. (II) Loadings: This is an industry measure useful for the determination of premiums. It reflects the firm's perception about customers riskiness and the expected size of liabilities in case accidents occur. (III) Year of car manufacture: This provides a measure of the age of insured cars. The range for this variable is between 1957-2015 in the sample. Thus the sample span a mix of both

---

[21](i) Summary statistics of the data are presented in Tables A2-A5 in the Appendix. (ii) The overall claims ratio is 22%. This reflect the amount paid out to insureds in comparison to premiums received by the insurer between April 2013 to May 2015. That is to say just GHC22 was paid out of every GHC100 paid in premiums, suggesting that "poor value for money" is given to policyholders. This number is by far below internationally accepted standards of 60%-80%. Clearly, under this schedule, it will be difficult to win the confidence of an average Ghanaian into insurance. This alleviates much worries about the entry of new customers. (ii) It can be misleading to directly compare claims for basic contracts to comprehensive contracts since insurers data for the former typically exclude some liabilities of own damages, in part. I address this following Chiappori et al. 2006. The details are in Appendix 9.3.

[22]One can imagine that insurees may fail to report claims in order to receive discounts and get lower prices, especially after the regulatory change. This is less likely since discounts are set to be less than claims. As I also show empirically, pre-regulation discounts and prices are distributionally similar to post-regulation discounts and prices – an evidence that speaks against potential under-reporting. Such information-hold up is usually termed "ex-post" moral hazard. The empirical analysis suggests that ex-post moral hazard is less, as compared to ex-ante moral hazard (unobserved loss preventive effort or behavior).

old and new cars. (IV) The make of car, body-type, coverage certificate-type as well as the transmission system are available.

I denote by X_{it} the vector of all controls. The control variables are helpful for improving the empirical analysis. The variables in category (IV) are available to the insurer, but these are not used in the pricing of insurance and therefore can be used to control for potential selection along such observable dimensions. One additional advantage is that the variables allow me to circumvent an empirical challenge which is discussed in Appendix 3.2. Next, part of the discussions about plausibility of the instrument's exclusion exploit changes in the distribution of these observed vector of characteristics.

Credit records: Finally, data on customer credit histories and outstanding premiums are available. Both the discussions and illustrations in Section 2 utilize this data.

4.2 Research Design: Strategy, exclusion Z, and balance

Strategy: In an ideal experiment designed to evaluate the effect of moral hazard, I would observe insurance outcomes for two similar consumers, then randomly assign one from comprehensive to basic contract ("treatment"), maintain the other on comprehensive contract ("control") and then compare changes in their insurance outcomes. The regulatory reform helps to mimic this condition. The no-credit regulation made one group of consumers switch to basic contracts (switchers or "treatment"), as exemplified by the remarkable decline and switch in purchases for comprehensive contracts in Figure 6 and Table 1. The rest of the consumers remained unaffected by the regulation (no-switchers or "control").

Exclusion and balance: With this strategy, it is crucial that the policy "instrument" be *excluded*, that is, conditionally independent of insurance outcomes.[23] An alternative way to

---

[23]First, note that this set up allows for adverse selection of any form, but the actual timing of the policy is unaffected by it. Second, this independence condition provides a direct means of (1) testing for the *absence* of moral hazard (Escanciano, Salanié and Yildiz 2016) and (2) bounding moral effects. In Section 5, I exploit this condition to construct a simple and general test for moral hazard's existence, while in Section 6, I use it as an exclusion for selection to derive worst-case and tight-bounds on the effect of moral hazard.

state this is:

$$Z \perp\!\!\!\perp [\alpha, \varepsilon] | (D, X)$$

In words, this says the *distribution* of the pair $[\alpha, \varepsilon]$ does not change after the reform, conditional on the relevant characteristics. This condition cannot be tested, so I will run robustness checks to show that the empirical design is valid.

Perhaps, the most important concern is that the actual timing of the regulation may have been anticipated by consumers and so might have reacted to it. For example, credit constrained customers can change their choices and other characteristics to make the effective difference in price between high and low coverage contracts negligible. Such responses can threaten the validity of the policy instrument and research design. Analogous to standard regression discontinuity RD design (Imbens and Lemieux 2008; Lee and Lemieux 2010), one can think of time as the running variable. This requires consumer characteristics to be similar at the policy cutoff to be valid. First, as shown in Figure 2, consumers did not expect the actual announcement of the regulation as credit decisions remained largely stable across the various months prior to its implementation. Second, Figures 7-10 jointly indicate a strong balance on the set of relevant control variables.[24] Specifically, the various distributions are not distinguishable at the policy cutoff.[25] Both lines of evidence suggest that the regulation was not anticipated.[26]

[Figure 7 about here.]

[Figure 8 about here.]

[Figure 9 about here.]

---

[24]These controls include variables that are used to price insurance and those that are not but observed. If the distribution of α (e.g., risk aversion) changes as a result of the reform, such changes might reflect in consumers characteristics. It is reassuring that observed consumers characteristics did not change around the policy. With the validity of the instrument's exclusion, I argue the reform "only" induced exogenous assignment of contracts which in turn affected customers' effort and other hidden actions.

[25]In a heterogeneity analysis, I estimate a simple model ($riskiness_{it} = \mu + \theta_r \text{Switcher}_{it} + \epsilon_{it}$) that compares the distribution of consumer riskiness score across switchers versus non-switchers, and find no significant differences between them ($\hat{\theta}_r = 57.1$ and $\text{SE}(\hat{\theta}_r) = 66.8$), as expected.

[26]Notice that if consumers anticipated the reform, they may have begun to alter their choices and other relevant characteristics prior to the reform. But if this were true, it would likely cause me to underestimate any effect the policy reform might have had because pre-reform claims would look more similar to post-reform claims behavior.

[Figure 10 about here.]

Another concern is that the timing of the regulation may correlate with current macroeconomic conditions and other factors that influence insurance claims. Notice that the data covers only two contract years, spanning contracts before and after the reform — implying a short period of time. First, I did a careful search of all related policies, and the records show that no other insurance reforms took place at around same time. Both α and ε can change if other insurance reforms took place over the period.

Next, the regulatory decision may reflect current economic conditions to likely confound the estimates. This would be an important concern if the reform could be implemented quickly. In practice, however, the implementation of insurance policies typically occurs with a substantial lag. For the no-credit regulation, there was a seven (7)-month lag in its implementation as shown in Figure A4, further strengthening the case for the validity of the policy change as an instrument.[27]

Consumer preferences α_i^u over insurance can change if customers switched to other insurance companies or insurers. This is less likely because prices are regulated and thus similar across firms, creating less incentives for consumers to move to other firms. As I discuss further in Sections 7.2 and 7.3, per-unit premium and market share for the company that provided the data remained unchanged after the policy. In addition, the no-credit regulation was a national reform that affected all companies so there is little reason for consumers to switch.[28]

Finally, individual heterogeneity that come from the production function α_i^y and ε can change if relevant macro conditions like recessions and floods occur, respectively. Major recessions for instance may lead to changes in gas prices and therefore could cause customers

---

[27](i) Reassuringly, the main results are robust to narrow time windows around the reform's introduction: ± 4 months before and after the regulation. (ii) The timeline of the regulatory reform is illustrated in Figure A4 of the Appendix. As shown, the NIC agreed on the policy on October 12, 2013. The implementation or announcement took place on April 1, 2014, yielding an implementation lag of about 7 months.

[28]Consumers who were owing companies might want to move to other firms. However, this seems unlikely given the higher repayment rate of premium debts and the fact that firms had to write-off all premiums outstanding after the regulation. From the sample, exiters represent only about 1.5% of customers. This is extremely low, as compared to the number of un-insured vehicles in Ghana (of about 2-1-36%), for example.

to switch to different cars e.g., to more efficient cars. While fluctuations in weather are common, no major floods occurred in the study area during the relevant period. In addition, I show in Figure A3 that changes in gas prices (direct pump prices) were not significant to actually induce customers to switch to different cars. In particular, the average and standard deviation for gas prices *before* the reform were USD/L 1.06 and 1.04, respectively. Similarly, the average and standard deviation for the prices *after* the reform were respectively USD/L 1.02 and 1.03; suggesting no significant changes.

5 A simple and general test of moral hazard

Section 4.3 argued that the variation induced by the introduction of the policy reform is conditionally independent of insurance outcomes: timing of policy is uncorrelated with unobserved heterogeneity. In this section, I use that exclusion condition to develop a simple generalized test for the *absence* of moral hazard in the insurance market. The analysis document evidence of moral hazard; baseline results that will supplement the subsequent results on moral hazard effects.

5.1 The moral hazard test

Consider the baseline set-up in the model, Section 3. The independence assumption provides a direct means of testing for the *absence of* moral hazard. To see this, assume that there is *no moral hazard*, $\partial g(.,.)/\partial e = 0$. Then one can write the implied system as

$$Y_{it} = g(\alpha_i^y, \varepsilon_{it})$$
$$D_{it} = \sigma(\alpha_i, Z_{it})$$
$$\rightsquigarrow Y_{it} \perp\!\!\!\perp Z_{it}|X_{it}$$

Without moral hazard, a change in coverage D_{it} induced by the reform Z_{it} and not by

selection does not induce a change in outcomes Y_{it}. Thus, one can test for the *absence of moral hazard* by testing for the independence between Y_{it} and Z_{it} conditional on all premium and non-premium determining consumer characteristics. In the implementation, Y_{it} is either continuous or binary while Z_{it} is binary. In what follows, I present the nonparametric testing procedure that I propose. Results for other candidate testing procedures are also reported.

I denote the conditional distribution function of Y_{it} given $Z = z$ by $F(y|z)$ and that given $Z_{it} = z'$ by $F(y|z')$. Similarly, let the un-conditional distribution of Y_{it} be $F(y)$. Then by definition: Y_{it} and Z_{it} are independent if $F(y|z)$ is equal to either $F(y|z')$ or $F(y)$. I exploit the use of this definition in the testing procedure described below. Next, denote the sum over all the binary values of Z_{it} by $\sum_Z$ and let $\pi(z)$ be the probability of realizing z. Then to test the hypothesis that there is *no moral hazard*[29] against the alternative that there is moral hazard, I construct the following L_2-Type test statistic

$$T = \sum_Z \hat{\pi}(z) \left[\sum_Y \left\{ \left(\hat{F}(y|z) - \hat{F}(y|z') \right)^2 \right\} \right]$$

where $\hat{F}(y|z)$ and $\hat{F}(y|z')$ are simply nonparametric empirical estimates of the conditional distributions which were predicted using the instrument Z, along with the relevant control variables X_{it}. In effect, the test statistic averages over the distribution of the decision variable Z_{it} and over the predicted outcomes Y_{it} (loss occurrence or claim amounts) of all the squared discrepancies between the two estimated distributional objects. The test allows the various values of Z_{it} to take different weights since they might occur with unequal chance.

The null is rejected for large values of T; in practice I derive the p-value of the test under the null hypothesis that there is no moral hazard using the nonparametric bootstrap. The bootstrap inference is conducted at a significance level of 5%. One shortcoming of this "Moral Hazard Test" is that it only provides inference about whether or not moral hazard is absent; it does not deliver the effect of moral hazard when the null hypothesis of *absence of moral hazard* is rejected. This caveat should be kept in mind when evaluating the implied results. Note here that the results from the test and two other candidate procedures should

---

[29]The null hypothesis can be stated as $H_0 : \{F(y|z) - F(y|z') = 0\}$ for any z, z' and y.

be seen not as a substitute but complementary to subsequent results on moral hazard.

5.2   Results

I begin by providing graphical evidence of the "Moral Hazard Test". First, the instrument and vector of controls are used to predict the conditional distribution of claim outcomes. Next, consider the various discrete values that the regulatory variable Z_{it} take. I divide the predicted sample of insureds into two groups based on the binary nature of the policy reform. I then define the claim distributions from the two groups as $\hat{F}(y|z)$ and $\hat{F}(y|z')$ where z and z' values correspond to pre– and post– National insurance reform, respectively. To fail to reject the underlying null hypothesis of "no moral hazard", it must be that these two distributions are equivalent.

In Figure 11, I plot the implied empirical cumulative distributions of claim outcomes pre– and post– insurance reform. This Figure provides visual evidence of the changes in the conditional distributions of claim outcomes. The graph in Figure 11 illustrates that there is a considerable difference between the distribution of predicted claim realizations before and after the reform. I can therefore reject the null hypothesis of no moral hazard.[30] In addition to the visual evidence of differences between distributions, the pre–reform distribution of claims tends to dominate that of the post–reform counterpart; suggesting that claim records became better due to the National reform. Altogether, the graph in Figure 11 provides a strong visual evidence of distributional inequality, and thus a rejection of the *no moral hazard* condition in this insurance market.

[Figure 11 about here.]

[Figure 12 about here.]

Finally, I evaluate the robustness of the graphical results by implementing the formal

---

[30]The inference is the same for alternative visual tests. In Figure 12, I compare the empirical distribution of claims (1) $\hat{F}(y|z)$ versus $\hat{F}(y)$ and (2) $\hat{F}(y|z')$ versus $\hat{F}(y)$. In both cases, there is substantial difference across the distributions; leading to a rejection of the null of no moral hazard.

nonparametric L_2-Type test proposed above.[31] I also considered a comparable nonparametric test of equality of distributions: Kolmogorov–Smirnov, along with other semiparametric methods e.g., OLS. The results are reported in Table 2. In all cases, the "Moral Hazard Test" strongly rejects the hypothesis that moral hazard is *absent* in this insurance market at conventional significance level of 5%. The Kolmogorov–Smirnov test provides similar inference. Overall, the results robustly suggest the existence of moral hazard. The following section investigates this further by bounding its effects.

[Table 2 about here.]

6   Bounding moral hazard under policy's exclusion

This section analyzes the separation and bounding of moral hazard effects. First, I build on the background formulation in Section 3 and policy's exclusion in Section 4.2 to provide identification results on moral hazard. Second, combined with the administrative data, I present the bounding results and discuss several dimensions of heterogeneity in moral hazard–important for insurance policy design.

6.1   Bounds on moral hazard effect

To conserve space, I summarize the main conditions and results. All details are relegated to the Appendix. The bounds set up embodies a triangular system in insurance outcomes and contract choice, as shown in the model section. Choice of contract depends on the exogenous policy or regulatory instrument, whereby it became impossible to buy insurance on credit. The restrictions required for the bounds are three-fold. The first is a weak–monotonicity condition, which requires that exerting higher levels of effort for a sub group of customers will not increase average claim outcomes. Such condition is a direct consequence of the Monotone Likelihood Ratio Property in Incentive Theory (Holmstrom 1979). The second is an independence condition, which implies no direct causal effect of the policy instrument

---

[31]The distribution of test statistic T is provided in Figure A2 of the Appendix.

on insurance outcomes, while the third condition requires that customers who select higher insurance coverage will not increase their supply of effort.

The starting point of the bounding exercise is to rewrite the average structural objects as a weighted average of observed and unobserved potential insurance outcomes, using insights from standard missing outcomes representation (Manski 1990; Manski and Pepper 2000). Introducing the instrument, which is independent of the potential outcomes, one can put bounds on the unobserved potential insurance outcome using the stated three conditions. The following proposition provides best possible bounds on moral hazard by combining all the restrictions.

Proposition 1

$$
\begin{aligned}
\Delta^l &= \sup_z\{\mathbb{E}[D_iY_i \mid Z = z] + \mathbb{E}[(1 - D_i)Y_i \mid Z = z]\} - \inf_z\{\mathbb{E}[D_iY_i \mid Z = z] + \mathbb{E}[(1 - D_i)Y_i \mid Z = z]\} \\
&= \sup_z\{\mathbb{E}[Y_i \mid Z = z]\} - \inf_z\{\mathbb{E}[Y_i \mid Z = z]\} \\
\Delta^u &= \inf_z\{\mathbb{E}[D_iY_i \mid Z = z] + (1 - P(z))G^u\} - \sup_z\{P(z)G^l + \mathbb{E}[(1 - D_i)Y_i \mid Z = z]\}
\end{aligned}
$$

The derivation of proposition 1 is provided in the Appendix. First, proposition 1 shows that the lower bound on moral hazard's effect is a simple difference estimator. Second, the bounds are made up of three estimable terms which include an insurance choice probability object $P(z)$ and two conditional expectations. I apply the results to credibly test and quantify the effect of moral hazard. The restrictions provide useful improvements to identify the lower bound Δ^l, so that will be the main object of interest. Before presenting the evidence, I briefly discuss motivations for the bounding approach in the following.

6.2 Why the bounding of moral hazard

The bounds are meant to nonparametrically identify and capture the range of moral hazard that cannot be explained by the usual point estimates approach, although the latter could provide exact statements about moral hazard e.g., I am able to characterize the minimal ex-

tent of moral hazard using the bounds. The bounds approach is motivated by the following. First, nonparametric point identification of moral hazard is hard to achieve under significant selection in and out of insurance without stronger and perhaps non-verifiable assumptions (additivity of selection α_i, for example). This becomes even more difficult when the dimension of selection in multidimensional – natural in an insurance setting. Second, the bounds allows me to also learn about the population. This provides a useful way to evaluate the impact of moral hazard, which is crucial particularly for the implied policy analysis that I illustrate later in this paper.

The proposed bounds approach allows unobserved heterogeneity, a vector of hidden information, to impact insurance outcomes in an unrestricted manner. I am therefore able to characterize moral hazard by fully accounting for differences across the individual customers insurance choice while allowing for arbitrary correlations with the insurance choice, and thus accounting for adverse selection.

6.3 Estimating the moral hazard effect

The focus is on bounds to the average treatment effects ATE, the measure of moral hazard effect, under the agency theory-inspired inequality restriction. Estimating the bounds requires two sets of intermediate estimators, one for the "insurance" probability and the other for the conditional expectation objects. In what follows, I briefly describe the estimation procedure that I employ.

As in the Sections 3 and 4, I index an customer (insured) by i and time (contract date) by t, and let hatˆdenote estimated objects throughout. Then the probability of "insurance" (comprehensive contract) purchase for an customer with characteristics z is estimated using the frequency estimator

$$\hat{P}(z) = \frac{\sum_i \sum_t \mathbf{1}(D_{it} = 1)\mathbf{1}(Z_{it} = z)}{\sum_i \sum_t \mathbf{1}(Z_{it} = z)}$$

where $\mathbf{1}(A)$ is an indicator that is equal to 1 whenever A holds and 0 otherwise. To estimate

the conditional expectation objects, I use sample-analog-type estimators

$$\hat{\mathbb{E}}[Y_{it}D_{it} \mid Z_{it} = z] = \frac{\sum_i \sum_t y_{it}\mathbf{1}(D_{it} = 1)\mathbf{1}(Z_{it} = z)}{\sum_i \sum_t \mathbf{1}(Z_{it} = z)}$$

$$\hat{\mathbb{E}}[Y_{it}(1 - D_{it}) \mid Z_{it} = z] = \frac{\sum_i \sum_t y_{it}\mathbf{1}(D_{it} = 0)\mathbf{1}(Z_{it} = z)}{\sum_i \sum_t \mathbf{1}(Z_{it} = z)}$$

where all notations match with those in Section 4 and the Appendix. The version of these quantities that condition on the conditioning vector X_{it}, including $\hat{\mathbb{E}}[Y_{it}D_{it} \mid Z_{it} = z, X_{it} = \bar{x}]$ and $\hat{\mathbb{E}}[Y_{it}(1-D_{it}) \mid Z_{it} = z, X_{it} = \bar{x}]$ are equivalently estimated using standard techniques. Y_{it} should be taken to be either claim outcomes or loss occurrence realized by customer i at time t. Next, the estimated objects above are then substituted into the identified best possible bounds for the average treatment effect Δ. This derives estimates of the lower and upper bounds under the agency theory-inspired inequality restriction, $\hat{\Delta}^l$ and $\hat{\Delta}^u$, respectively. Appendix A.1 provides an illustration of the various terms.

To conduct inference, I construct the confidence intervals for the parameters of interest Δ^l and Δ^u using the nonparametric bootstrap. In general, the bootstrap relies on continuity. This should be valid here since the estimated objects correspond to functionals for which regularity conditions for the bootstrap are met and I apply the sup and inf operators over a binary/finite support variable. Here the sup and inf are essentially max and min operators given the finite support of the instrument Z. In practice, I conduct the bootstrap inference at 5% level of significance while fixing the number of bootstrap resamples to 999 throughout.

6.4   Results

The main empirical results are reported in this section. The baseline estimates of average treatment effect, the measure of moral hazard effect under the agency-theory inequality restriction are presented. More specifically, Table 3 reports both the lower and upper bound estimates on moral hazard for two insurance outcomes.

[Table 3 about here.]

Estimates that correspond to loss probabilities are displayed in the left panel, while those for insurance claims are presented in the right panel of Table 3. The 95% confidence intervals which are based on nonparametric bootstrap are also reported in the last column of each panel. As shown in Section 3.2, evidence of moral hazard requires the average treatment effect which measures moral hazard to be greater than zero. This is equivalent to saying that customers' claim outcomes (or loss occurrence) increase with respect to insurance coverage on average after selection is eliminated. Similarly, the effect of moral hazard e.g., minimal or maximal extent can also be deduced by looking at magnitudes of the estimated quantities.

6.4.1 Evidence of moral hazard and effects

More generally, the estimates in Table 3 provide strong evidence of moral hazard in the insurance market. In particular, I find evidence of moral hazard for both outcomes of interest: loss occurrence and insurance claims. The estimated lower and upper bounds on moral hazard are GHC52 and GHC108172, respectively for claim outcomes. The estimated lower and upper bounds on moral hazard are 1% and 77%, respectively for loss occurrence.[32] The 95% confidence intervals around the estimates are quite narrow.

Section 6.1 and Appendix A.2 show that the identifying power from the inequality restriction improves only the lower bound of the unknown quantity $\mathbb{E}[Y_i(1) \mid D_i = 0, Z = z]$ and the upper bound of the unknown $\mathbb{E}[Y_i(0) \mid D_i = 1, Z = z]$. In turn, these two improvements together provide a *lower* bound estimate on moral hazard. Restricting attention to the lower bound, moral hazard effects are derived as follows. For claim outcomes, the minimal moral hazard estimate of GHC52 translates to about 46% of average claims over the sample period. In other words, moral hazard accounted for *at least* 46% (lower bound) increase in realized mean claims. The same reasoning *mutatis mutandis* implies that moral hazard was responsible for *at least* 22% of the probability of loss occurring over the period (using the moral hazard estimate of 0.87%). These results point towards a strong moral hazard

---

[32]The upper bound is very high because the identifying restrictions do not improve the terms that comprise it. It is rather made up of objects that reflect the empirical maximum for claims, which can be higher.

effect and suggest moral hazard affects changes in claim amounts "as much as" occurrence of losses. Overall, the moral hazard evidence is robust across various definitions of insurance outcomes.

6.4.2 Sources of moral hazard, visually: ex-ante versus ex-post effects

Section 3.2 points to two potential sources of moral hazard: ex-ante and ex-post aspects. I assess these visually by looking at observed changes in the type of claim events before and after the policy reform. Figure 13 (a) and (b) show how the claim events not covered under basic contracts and those covered under both contracts are distributed, respectively. The results suggest about 35.8 percent drop in the set of claim events that are covered by only comprehensive contracts after the regulation. Such policy-induced reduction likely reflects ex-ante moral hazard (i.e., unobserved preventive actions) because all things being equal, it seems reasonable that under-reporting of claims is less likely for comprehensive contracts that provide coverage for all responsible losses.

There is evidence that claim events that are covered under both basic and comprehensive contracts dropped by 29.6 percent after the policy. This drop likely reflect ex-post moral hazard (i.e., under-reporting claim or information) along with with ex-ante effects. Overall, the results indicate that both sources of moral hazard are present. However, observe that ex-post moral hazard has an opposing effect on the "frequency" of reported claim events. In part, this explains why the reduction in claim events that are covered under both contracts (29.5%) is lower than those covered under only comprehensive contracts (35.8%). With this, only 6.3% drop in claim reports is attributable to ex-post moral hazard; suggesting that under-reporting is less severe. Finally, note that since basic-liability reports involve third parties, it is difficult for consumers not to report such events.

[Figure 13 about here.]

33

6.4.3 Conditional estimates: moral hazard effects

Some papers study one informational friction (say, adverse selection) by abstracting from the other. For example, Cohen and Einav (2007) abstracted from moral hazard and focused on adverse selection in auto insurance contracts.[33] Since the background model allows for both moral hazard and adverse selection, I can conveniently analyze the implications of such abstractions. To do this, I assume that adverse selection is absent, and then estimate moral hazard. Without adverse selection, the lower bound on moral hazard is a "naive" estimator which takes the form

$$\equiv \max_d \mathbb{E}[Y_i \mid D = d, X = \bar{x}] - \min_d \mathbb{E}[Y_i \mid D = d, X = \bar{x}]$$

The results are reported in Table 4 separately for loss and claim outcomes. Both indicate large and significant moral hazard effects. Strikingly, compared to the main credible estimates of moral hazard, these results are 4-7 times bigger. In addition, the selection effect which captures the bias introduced by not randomizing contracts is large. This is about 0.03 for the occurrence of losses, and GHC320 for claim amounts. This analysis show that assuming away adverse selection have nontrivial effects and vice versa. Moral hazard is over-estimated in substantial magnitudes, but this may depend on the direction of selection.

[Table 4 about here.]

6.4.4 Heterogeneity in moral hazard

The moral hazard estimates may be heterogeneous in at least two observable dimensions (i) private versus commercial vehicle drivers, and (ii) different quartiles of discounts–reflecting the relative position of customers on the distribution of premium discounts that customers receive from the company. Private vehicles embody individual and corporate vehicles, while commercial vehicles are mostly taxis and mini-vans. Notably, individual vehicles usually

---

[33]Adverse selection is modeled as unobserved heterogeneity in risk preferences (riskiness and risk aversion) from the choice of deductible in contracts using data from Israel.

contain the vehicle's owner and his driver. I assess such potential heterogeneity by providing lower bounds on moral hazard by driver type and by quartile of discounts – the results of which can help guide policy design and discussions about the automobile insurance market as well as simulate further related research.

In Figure A1 of the Appendix, I show the heterogeneous estimates on moral hazard. Similar to the main results from Table 3, I can reject the null of no moral hazard at 5% level of significance across all driver types and quartiles. The moral hazard estimates are larger for both commercial vehicle and lower quartile discount drivers, which in turn suggest that commercial drivers and low premium discount customers are less responsible. In this case, corrective policies to influence moral hazard can include schemes that make basic insurance contracts more attractive to the subgroup of customers associated with commercial vehicles, e.g., weighed against the potential cost of subsidizing insurance for this group.

Next, the heterogeneous results can be related to the concept of monitoring and moral hazard. Private vehicles usually operate with two people, typically the car's owner (who may act as a "monitor") and his driver.[34] For commercial cars, this is not the case as they do not run with the owner. In this case, the availability of a "monitor" in private vehicles can explain why private drivers are more responsible than their commercial counterparts. As a result, the heterogeneous findings generally imply that "monitoring" can be an effective tool in curbing moral hazard, which is consistent with theoretical results in Holmstrom (1979) and others.

7   Mechanisms, caveats and policy implications

In this section, I discuss the role of two potential channels for contract choice and their importance for shaping the estimated incentive effect: moral hazard. These include liquidity constraints and changes in relative prices. There is evidence in favor of the former; not the

---

[34]The owner of the vehicle do not only observe and serve as a "monitor", but can also fire the driver when he drives recklessly at a low to zero firing cost.

latter. First, I illustrate that moral hazard increases with the probability of buying insurance on credit; providing additional evidence of heterogeneity in moral hazard. I then discuss how this heterogeneity is consistent with credit constraints. Next, I carry out an array of tests to verify that the main results are robust to several caveats. The broader implications of the estimated quantities are also presented.

7.1 The role of credit constraints

Before presenting the evidence, I note why borrowing may be limited for the customers who bought insurance on credit. First, there is evidence indicating that the customers who purchased insurance on credit switched to contracts with lower coverage after the reform. So if they could borrow, they would have done it to seek contracts with higher coverage after the reform. In addition, interest rates are high in Ghana, at least compared to interest rates in developed economies like the United States and Canada over the period. For example, interest rates in Ghana averaged about 20% between May 2013 and April 2015, compared to the United States average rate of $< 1\%$.[35] This removes the incentive to borrow to buy higher contracts.

I now document the relation between moral hazard and the purchase of insurance on credit. There are potentially multiple ways to investigate how the provision of credit ultimately shape the estimated moral hazard effect. The direct approach will be to split the sample into sub groups of customers who bought insurance on credit and those who paid insurance upfront, and then estimate moral hazard for each sub group. The second approach involves using information about the credit-purchases/history of consumers to identify the distribution of those who are likely impacted by the regulation, and then compare moral hazard effects across this distribution. Here, I follow the latter approach because implementation of the former is limited by the way the policy instrument Z is constructed and the fact that after the reform's introduction consumers could no longer buy insurance on credit. I am also

---

[35]For example, see https://tradingeconomics.com/ghana/interest-rate for Ghana, and https://www.oanda.com/forex-trading/analysis/historical-rates for the United States and Canada.

able to examine whether or not changes in the moral moral effect is monotonic along the distribution of credit decisions.

Denote by $P(c^r; x)$ the probability that a customer with observable characteristic $x = X_{it}$ acquires insurance on credit. Extremely low $P(c^r; x)$ corresponds to customers for which credit is not important; and thus will not be affected much by the reform. Equivalently, high values of $P(c^r; x)$ correspond to customers for which credit is important. I proceed in two interrelated steps. First, I estimate $P(c^r; x)$ by estimating a probit regression model of whether or not an customer purchased insurance on credit against the observable vector of individual characteristics. This estimation is done using the universe of customers in the sample for both contracts, $D_{it} = 1$ and $D_{it} = 0$. The estimated credit probabilities are displayed in Figure 14(a). The figure shows a range of probabilities that lie between 0% - 41%, with a median of about 8%. This means that the median consumer with observable characteristic x is 8% likely to purchase insurance under the credit schedule. Also, in Figure 14(b) I display the distributions of estimated credit probabilities across the two contract types. There is evidence that consumers were more likely to use credit to purchase contracts with higher coverage before the no-credit regulation.

[Figure 14 about here.]

In the second step, I investigate the effect of buying on credit by estimating the lower bound on moral hazard (i) separately for the group of customers who fall below versus above the median credit probability, and then (ii) across the different quartiles of the credit probabilities. The results are displayed in Tables 5 and 6, respectively. First, there is evidence that the moral hazard effect is larger for the customers below the median probability, compared to those above. For claim amounts, this is about 5 times larger, while for loss occurrence it is about 2 times larger. Second, the effects across the credit distribution is non monotonic, but much of the moral hazard is concentrated in the upper credit quartiles as expected.

These results are intuitive. Credit matters more for consumers in the upper quartiles since they are likely credit constrained. The impact of the no-credit regulation should be more binding for this group. As illustrated in Figure 14(b), the customers who were purchasing comprehensive insurance more likely do so on credit than those who were buying the basic contracts. This explains why most customers switched from comprehensive to basic contracts following the reform (see Figure 6 and Table 1). The incentive to shirk is higher under the comprehensive contract. These results support the hypothesis that consumers responses to the reform likely through the "liquidity" mechanism. Finally, note the primary trade-off of sub sampling customers based on credit quartiles for the analysis: uncertainty increases because the size of the sample is reduced drastically.

[Table 5 about here.]

[Table 6 about here.]

Discussions: Are these effects due to credit constraints or financial saviness? In principle, consumers' credit decisions can reflect the two, so both explanations are possible. The latter will mean that customers were gaming the system of buying on credit, with no intentions to repay their accrued premium debts. If this was the case, then that will imply possibly another moral hazard via defaults/delinquencies from the credit side. However, the evidence is more consistent with credit constraints as discussed below.

Credit constraints are a natural reason for explaining the drop in insurance demand after the reform and thus the moral hazard results. This is for several reasons. First, as I argued earlier, the policy reform tightened liquidity and affected consumers who were buying insurance contracts on credit prior to the introduction of the reform. In particular, over 99.4% of consumers who were buying insurance on credit bought higher-coverage contracts and switched to contracts with lower coverage after the regulation. So, consumers' responses to the reform most likely operate through this "liquidity" mechanism.

Second, there is much evidence that people in developing countries face liquidity con-

straints (Banerjee 2001, Banerjee and Duflo 2011; Karlan et al. 2014). For example, Karlan et al. 2014 documented credit constraints in northern Ghana.[36] Third, as I documented in Section 2, the repayment rates for premium debts are substantially high. For example, 79% of customers who bought insurance on credit repaid their outstanding premiums before their contracts expire. Similarly, over 73% of all outstanding premiums are paid before the end of the insurance contract. These results are less consistent with financial saviness, lending further support to the credit constraints channel.

7.2   The role of firm price response

In principle, insurance firms may respond in multiple ways to the National reform via the differential pricing of contracts e.g., increase overall premiums to maintain certain levels of profit; decrease premiums for comprehensive coverage to encourage their take up; discourage basic contracts through increases in price for such coverage; or employ other response strategies that will manifest through prices. Such supply side responses can reflect the moral hazard results. I document that the insurance company did not significantly adjust per-unit premiums following the introduction of the reform. This finding helps to shut down the possibility of an alternative mechanism ("price") and lends further support to the "credit" channel argument.

I begin with a descriptive analysis of the changes in prices. In Figure 15, I show both the distribution and differential changes in insurance premiums before and after the policy reform. In the first row, the first item scatters realized premiums over the period, while the second centers these at the policy date. The scatter has been jittered to make it is easier to see where the mass is located. There are two important observations: the mass is evenly distributed and there is no evidence of significant differences in premiums around the

---

[36]Theoretically, the credit-constraints channel can be understood formally in a model where consumers make insurance and effort decisions today subject to the risk of a liquidity shock tomorrow, akin to the setting of the policy reform (similar to Deaton 1991). The simple intuition is that because the agent cannot borrow to buy more insurance when the liquidity shock arrives and effort is costly (in monetary terms), the agent likely demand more insurance today and exert less effort. In that case, accumulated net income transfers from insurance can be used to smooth future consumption.

reform's date. To account for the possibility of differential pricing across contracts, I show changes in realized premiums for the two contracts in the second row. However, the changes are also visually insignificant.

[Figure 15 about here.]

Next, I evaluate the robustness of the descriptive evidence using a model that links changes in premiums to contract years and coverage. For consumer i in contract year t, the simplest model that I estimate is:

$$\rho_{it} = \mu_i + \delta \text{Policy}_t + \epsilon_{it}$$

where $\text{Policy}_t = \mathbf{1}[Date > \text{April 2014}]$. Figure 16 displays the distribution of premiums after customer-level fixed effects μ_i are removed from the data (distribution of $\delta \text{Policy}_t + \epsilon_{it}$). This is shown for the period before and after the 2014 insurance regulation. The figure demonstrates limited evidence that premiums changed following the policy, similar to the descriptive evidence. The estimated $\hat{\delta}$ is 18.67 and insignificant at conventional levels. I modify the baseline model to investigate differential pricing using:

$$\rho_{it} = \mu_i + \beta [D_{it} \times \text{Policy}_t] + \gamma \mathbf{X}_{it} + \epsilon_{it}$$

where D_{it} and Policy_t are respective indicators for higher coverage and post regulation period. The model essentially interacts the two indicators. β, the main parameter of interest, captures the sign, size and significance of any differential pricing by contract-type following the reform. All relevant control variables are housed in the vector $\mathbf{X}_{it}$ (i.e., the list of observed characteristics discussed in Section 4.1).

The results are reported in Table 7. Different columns correspond to different model specifications, based on the inclusion of the various control variables. The coefficient on the interaction term is negative and insignificant at conventional levels in the preferred specification, column 3 where all premium-determining characteristics are included. Results indicate that on average firms did not alter the premiums deferentially, all else equal. Taken

40

together, these results provide suggestive evidence of no significant price responses. This is expected given that the NIC strictly regulates the pricing of insurance products. Results reinforce the explanation that the estimated moral effects are driven by credit constraints.

[Figure 16 about here.]

[Table 7 about here.]

7.3 Robustness Analysis

Threats from sample selection: The "ideal" data set to evaluate moral hazard will embody the universe of contracts data across all firms in the insurance industry. In this paper, I mimic this using customer-level data from the single largest firm: largest branch (headquarters) office records. A drawback of this approach concerns the representativeness of the sample due to potential exits and entries of customers across insurance companies. More specifically, the sample suggests about 1.5% and 3.7% rate of exits and entries, respectively.

First, what works is that relevant changes in the industry and aggregate outcomes are largely consistent with evidence from the sample. As shown in Figures 17-19: (i) the market share of the study-company remained stable at 22% between 2013 and 2014; suggesting less drastic movements in and out of the firm overall; (ii) consistent with the sample, there is evidence of overall reduction in motor crashes or losses between 2013 and 2014; and (iii) there is evidence of general reduction in claim amounts and increased profits between 2013 and 2014 as in the sample. This line of aggregate evidence is re-assuring and lend further support for the empirical results. Second, the baseline results are stable using a restricted sample of customers who existed in the data before and after the policy (balanced sample; see analysis below). The implication of this result is that potential entry of new customers likely have less severe effects on the main moral hazard results.

[Figure 17 about here.]

[Figure 18 about here.]

[Figure 19 about here.]

Entry & exit of new customers In practice, different customers could either enter or exit the insurance pool after the reform's introduction. I investigate how this, particularly entry, might affect the results by limiting the estimations to the set of customers that maintained the same policy numbers before and after the policy reform. As shown in Section 4.2, (i) pre-reform distributions of customer characteristics are similar to post-reform distributions and that (ii) it is unlikely for customers to leave the insurance pool for other insurance companies since prices are the same across firms, so I do not expect significant changes to the results. Figure 20 shows the conditional distribution of predicted claims, while Tables 8 and 9 present the bound estimates for moral hazard and across the group of customers below and above the median credit probability. In all cases, the evidence is qualitatively similar. Notably, there is evidence of larger moral hazard effect for customers below the median credit probability (constrained) as compared to the unconstrained.

[Figure 20 about here.]

[Table 8 about here.]

[Table 9 about here.]

Restricting the analysis to only third-party events In Appendix A.3, I discuss the approach used to recover comparable claim records for basic-liability contracts, since the insurer data typically do not capture own damages directly for customers with basic-liability insurance. But because the insurer data includes damages for third-party events which are covered under all contracts and directly available, I evaluate the robustness of the main results by limiting the analysis to only third-party claim events. As shown in Table 10, the estimated moral hazard effects are near and well within the confidence intervals of the main

estimates. For the size of claims, the lower bound estimate translates to 39.10% of mean claim amounts, while for the number of claims, it translates to 16.58% of loss probabilities.[37]

<center>[Table 10 about here.]</center>

Narrowing the window of analysis Section 4.3 appealed to the short period of data coverage to argue for the reform's independence to selection. As an alternative, I examine the stability of the baseline results using data right before and after the policy reform. This minimizes the influence of realizations that occurred far from the reform, but implies a drastic reduction of the sample size. Instead of the full sample, two time windows are considered (i) ±8 months and (ii) ±4 months windows around April 2014. Figure 21 displays the distribution of predicted insurance outcomes for the different windows; a test for moral hazard. The bounds on moral hazard are summarized in Table 11. The graphical evidence suggests stronger rejection of no moral hazard, but qualitatively these results are similar to the main findings. The bound estimates are very close and well within the confidence intervals of the main estimates.

<center>[Figure 21 about here.]</center>

<center>[Table 11 about here.]</center>

Effect of outliers I winsorize the data to reduce the influence of extreme claim and loss realizations. All observations in the data below the 2.5th percentile are set to the 2.5th percentile value, and those above the 97.5th percentile are set to the 97.5th percentile value. This approach minimizes the influence of extreme observations, but censors the data. I replicate Figure 11 and Table 3 using the winsorized data. Results pertaining to the moral hazard test are shown Figure 22, while the bound estimates are contained in Table 12. Both the graphical and bounds evidence are near and consistent with the main findings.

---

[37]Such evidence is consistent with less-severe under-reporting of claim events (as discussed in Section 6.4.2) in the baseline analysis that uses events under comprehensive contracts to recover claims for basic contracts for comparison. This may be explained by the nature of third-party events: they involve other customers, making it difficult for responsible policy holders not to report their occurrence. It also helps to alleviate potential concerns that the baseline exercises are just picking up less reported but not actual damages. Finally, note that since the baseline analysis combine all claim events (third-party and own damages), it is expected that limiting the estimations to only third-party damages will yield slightly lower estimates for moral hazard.

<center>43</center>

[Figure 22 about here.]

[Table 12 about here.]

Effects from externalities The model and bounds assume independently distributed accidents. In practice, however, external effects from others driving activity can violate this independence. For example, one consumer can hit another and then run away. First, this would be a major concern if such external effects vary with switchers versus non-switchers (or the quasi-assigned contracts). In particular, the main estimates will be biased downward if the external effects for non-switchers are systematically larger than the switchers and vice versa.[38] But to the extent that these externalities are possibly random, that seems unlikely. Second, when an accident occurs, there is often one party who is at fault (or the liability is shared) based on the legal statutes. The functioning of legal systems in low-income environments may be weak, but existence of such legal arrangements help to internalize part of the external effects.

Third, I use the following back-of-envelope calculations to assess the potential magnitude of such external effects. The effects correspond to the additional costs of accidents beyond observed claims. Following Cohen and Einav (2007), I estimate this by dividing the (i) total accidents (18,050 in 2013; 14,895 in 2014), and (ii) accidents with fatalities (1,898 in 2013; 1,806 in 2014) in Ghana[39] by an estimate of the total number of auto insurance claims (48,809 in 2013; 45,238 in 2014) in Ghana.[40] For 2013, I find that 36.9 percent of claims involve reported accidents, and 3.9 percent involve accidents with fatalities. For 2014, 32.9 percent of insurance claims involve reported accidents while 3.9 percent involve

---

[38]Equivalently, the estimates will be biased download if the external effects before the policy are larger than effects after the policy. This can be seen from a modification of the lower bound estimator: $\triangle^l + \{\mathbb{E}[E_{z0}]\} - \{\mathbb{E}[E_{z1}]\} = \triangle^{l*}$ where $\mathbb{E}[E_{zj}]$ corresponds to the average external effects before ($j = 0$) and after ($j = 1$) the policy reform, and $\triangle^{l*}$ is the true population parameter of interest.

[39]Accidents refer to crashes resulting in injury, death or property damage and involves at least one vehicle on a public road. These are reported to the police and a police officer arrived at the scene. The data come from the National Road Safety Commission (NRSC) http://www.nrsc.gov.gh/

[40]The total number of car insurance claims are estimated by dividing the total number of insurance policies at the end of the sample (~30,000) by the product of the share of the market for the company that provided the data (21%) and the best guess of the share of policies from the company's headquarters branch (12%) where the contracts data come from. I then multiply this by the insurance claim or loss rates before and after the policy: 0.041 in 2013 versus 0.038 in 2014, respectively (see Tables A3 and A4 of the Appendix).

accidents with fatalities. This implies that the majority of insurance claims embody small unreported accidents,[41] perhaps because the additional external effects are often small. In addition, the calculations indicate modest reductions (but insignificant) in external effects after the regulatory reform, perhaps suggesting that the main estimates are (negligibly) biased downward.

7.4 Welfare implications: moral hazard and policy

7.4.1 Estimating foregone claims bill due to moral hazard

The baseline lower bound estimate of moral hazard is informative and have important broader implications first on the insurance market, and second on the National reform itself in general. More specifically, the reform-identified estimates generate impacts that are of further economic significance. The Cedis GHC52 sounds small but actually it is not because it represents a large fraction of average payouts over the period $\hat{\gamma}^{MH} = 46\%$, which is further explored, below.[42] As an illustration of the GHC52, let's suppose customer i has a basic contract $D_i = 0$, and let the insurer *randomly assign* this customer to the comprehensive contract $D_i = 1$. Then the GHC52 is the added loss that the company will have to cover. This follows because all losses are covered under the comprehensive plan. The above process could translate into large actuarial losses and thereby limit the soundness of the actuarial process.

To illustrate and put the results into context, I examine (the mean of) observed indemnity payments that may be attributed to moral hazard using the lower bound estimate of moral hazard. Since actuarial indemnities are largely based on claim outcomes which in turn reflect insured private information, I generally define the indemnity function as

---

[41]Note the consistency of with the initial evidence in Section 6.4 that under-reporting is likely less severe.

[42]*Note*: The GHC52 estimate also translates to about $\hat{\gamma}^{MH}$ =12% of firm's average profits. Here, average profits is given by $\Omega = \bar{\mathbb{E}}(\rho_{it}) - \bar{\mathbb{E}}(\iota_{it}) \times (1 + \lambda)$ using a simple back-of-envelope calculation. $\lambda = 0.25$ denotes the loading on payouts. To get this, the observed premiums and indemnities from the insurer's data set are directly used to compute expected revenues $\bar{\mathbb{E}}(\rho_{it})$ and expected costs $\bar{\mathbb{E}}(\iota_{it})$, respectively. This calculation ignores any direct returns on company investments of collected insurance premiums.

$$\iota_{it} = h_{it}(Y_{it}|\gamma^{MH}, \alpha^{AS}; \varepsilon)$$

for customer i at contract year t, where α^{AS} and γ^{MH} correspond to the vector of hidden information as discussed in the model section and estimated moral hazard, respectively. Then to obtain the average of indemnities for the population of insured, I take expectations over i and t to get

$$\mathbb{E}(\iota_{it}) = \int h_{it}(Y_{it}|\gamma^{MH}, \alpha^{AS}; v)dH(Y_{it}|\gamma^{MH}, \alpha^{AS}; \varepsilon)$$

where $H(.|.,.;.)$ is the conditional claim distribution. Obviously, one needs to estimate this object in order to compute the average of the indemnities which is fraught with much difficulty. Instead of directly estimating that, I utilize the actual paid indemnities in the sample. In estimating the effect of moral hazard, I jointly allowed for an unrestricted selection in and out of insurance: this significantly controls for/eliminates adverse selection and other important drivers of the indemnities. This therefore permits me to compute the fraction of indemnities paid to customers due to moral hazard using the sample analog[43]

$$\bar{\mathbb{E}}(\iota_{it}|\alpha^{AS}; \varepsilon)^{MH} = \hat{\gamma}^{MH} \times \sum_i \sum_t \bar{\iota}_{it}$$

where bars $^-$ are used to denote sample realizations here. $\hat{\gamma}^{MH}$ stands for the estimated moral hazard as a fraction of realized mean claims over the period. The implied dollar values are directly derived–reflecting the corresponding *actuarial losses* due to moral hazard.

Moral hazard accounted for *at least* GHC1,328,138 (USD442,712)[44] aggregate leakages or forgone bill in indemnities for the auto-business line of the company's branch between the two contract years. From additional back-of-envelope exercises, I find that the forgone bill for the insurance company is GHC11,067,817 (USD3,689,272), and for insurance industry is

---

[43]In effect, I am measuring the total rather than marginal contribution from the reform-identified moral hazard. The approach is technically equivalent to: GHC52×#ofConsumers.

[44]Prevailing exchange rate 1.00USD ≈ 3.00GHC. See https://www.oanda.com/currency/average

GHC52,703,889 (USD17,567,963).[45] This analysis highlights the potential soundness of the National reform because of the implied actuarial gains. As an interpretation: moral hazard accounted for a significant share of insurance claims, which induced substantial leakages in claims (inefficiencies). To the extent that the National reform exogenously caused consumers to switch to less generous contract choices, the reform arguably averted this extent of market inefficiency.

7.4.2 Estimating effects on welfare

The introduction of the policy reform is not only beneficial, but may generate unintended costs on consumers. Specifically, the no-credit regulation has two potential implications for welfare. First, because the reform led to lower coverage, it may have negative welfare implications for consumers. Second, as I highlighted in Section 7.4.1, ending the purchase of insurance on credit have positive welfare implications for firms via increases in profits due to reduction in large moral hazard inefficiencies. I compare these two opposite forces to evaluate whether or not the policy was welfare decreasing, overall.

I use the certainty equivalent as a measure of consumers welfare. Denote by $c_{it}(d) = Payouts_{it}(d) - Premium_{it}(d)$ the net transfer from insurance to consumer i under coverage d. I assume a constant absolute risk aversion (CARA) utility function with coefficient of absolute risk aversion $\gamma > 0$:

$$u(c_{it}) = -exp^{-\gamma c_{it}}$$

from consuming a normally distributed c_{it} in contract year t. The certainty equivalent per contract year is defined as:

$$CE = -\frac{1}{\gamma} \log \mathbb{E}(exp^{-\gamma c_{it}})$$

$$= \mu_c - 0.5\gamma \times \sigma_c^2$$

---

[45]For the company, I estimate the forgone bill by dividing the GHC1,328,138 by the best guess of the share of the company's headquarters branch where the contracts data came from (12%). For the industry, this is derived by dividing the company's bill by its share of the entire insurance market (21%).

where μ_c and σ_c are the mean and standard deviation of c. These are estimated using the empirical realization of net insurance transfers to consumers, separately before and after the policy reform. I then derive changes in certainty equivalents $\triangle CE$ by subtracting the estimated certainty equivalents post-reform from that of pre-reform. The results are displayed in Table 13 for different plausible values of absolute risk aversion γ. Relative risk aversion parameters between 2-5 are considered reasonable, so I divide this by the average annual earnings in Ghana in 2013/2014 to get reasonable values for γ.[46] These calculations indicate that the loss in consumer welfare attributable to the no-credit reform is between GHC111,559 (USD37,186) to GHC178,341 (USD59,447).

Next, I examine changes in firm profits due to the policy reform. Let $\pi_{it} = Premium_{it} - (1 + \lambda) \times Payouts_{it}$ represents the per-customer profit to the insurer. The total profit per contract year is given by:

$$\pi = \sum_i Premium_i - (1 + \lambda) \times \sum_i Payouts_i$$

where $\lambda = 0.25$ denotes the loading factor on payouts: typically, reflects the administrative costs of processing claims. Similar to the certainty equivalent calculations, I used the empirically observed premiums and payouts to compute changes in profits $\triangle \pi$ pre- and post-reform. As shown in Table 13, the gain in producer welfare attributable to the policy reform restricting the sale of insurance contracts on credit is between GHC1,023,168 (USD341,056) to GHC9,210325(USD2,302,581). Taken together, for reasonable values of consumer risk aversion, enforcement of credit arrangements and insurance loading, the analysis suggests that restricting the sale of insurance on credit have both negative and positive welfare implications but the loss in welfare do not outweigh the gains. The loss in certainty equivalents represents approximately 11% of the gain in profits for cases where some proportion or all premium debts are eventually repaid before the expiration of contracts.

---

[46]The estimate of average annual earnings in Ghana was GHC5,346.9 (GSS, 2013/2014). The implied parameter values are very close those provided in Cohen and Einav (2007). From the automobile insurance in Israel, the authors estimate mean absolute risk aversion of 0.0019; and a median 0.0000073.

8   Conclusion

In this paper, I argue that contractual arrangements that defer the payment of insurance premiums to a future period, not only increase demand but induce large moral hazard effects. The coexistence of moral hazard and adverse selection, possibly multidimensional in nature, presents a challenge in learning about moral hazard alone. I disentangle moral hazard from selection by exploiting a natural experiment coming from the introduction of an insurance reform, whereby it became impossible to buy insurance on credit, making lower coverage contracts more attractive. By requiring that car insurance premiums be paid upfront, the demand for higher coverage decreased by 6 percentage points.

The random variation created by the policy reform allows me to construct an instrument to identify the causal effect of coverage choice on claim amounts and loss occurrence—moral hazard—and eliminate contaminations that may be due to selection. I empirically investigate the identifying power of the weaker restriction that, on average, consumers that select higher coverage contracts will not increase their supply of effort. I find a convincing and robust evidence of moral hazard in this market. Moral hazard led to a 46 percent increase in average size claims or 22 percent increase in the number of claims. The analysis also establishes that moral hazard induced significant leakages in insurance claims and that monitoring can be an additional effective tool in curbing moral hazard.

I discuss two potential mechanisms that could be responsible for the moral hazard results: binding credit constraints versus changes in relative prices, and find evidence in favor of the former. In principle, this is equivalent to examining the channels through which the policy reform may shift choices of insurance contracts and thus moral hazard. Heterogeneity analysis suggest that the results likely operate through a constraint in "credit" that was imposed by the policy reform, where moral hazard is greater for the more credit constrained. This

result establishes an important connection between incentive effects and credit constraints. Finally, insurance firms may alter the pricing of contracts to maintain certain profit levels as a response to the policy reform. For example, decrease (increase) the premiums for higher (lower) coverage contracts to encourage (discourage) their uptake. I find no evidence across multiple tests for such differential pricing.

Examining the impacts of "buying on credit" on car insurance demand, credit and moral hazard has applications for other types of insurance. First, consider the case of personal insurance which is widely offered by private insurance companies. This insurance requires individuals to pay premiums upfront. The results in this paper directly imply that customers who face the risk of credit constraints are less likely to be responsible. In this case, an alternative policy to reduce moral hazard would be to make lower coverage contracts more attractive to the potentially credit constrained customers.

There are two additional indirect applications: social and index insurance. For social insurance programs, no upfront premium payments are involved but may embody potential moral hazard and liquidity aspects. Examples include unemployment insurance and social interventions. Studies and design of social programs tend to consider moral hazard and liquidity as separate entities (Chetty 2008). The results in this paper indicate a potential linkage between the two; thus extending our knowledge about moral hazard and liquidity for program designs. For weather index-based insurance, moral hazard is largely absent—since contract payments are based on an exogenous publicly observable index, such as local rainfall, paying out on the basis of too much or too little rain—but liquidity constraints may be present to impede uptake (Cole et al. 2013; Karlan et al. 2014). A conventional policy may overcome credit constraints to induce insurance uptake (Casaburi and Willis 2017), but as shown in this paper, it is crucial to consider the potential moral hazard aspects when present. For this reasons, policy instruments e.g., loan programs, that aim to increase demand will require full benefit-cost assessment to justify their implementation.

From a policy perspective, two aspects are notable. First, this paper illustrates how regu-

lation can be used to fix insurance market imperfections, particularly, insurance in developing countries. The moral hazard effect translates to about a 12% decline in firm profits, but such inefficiency was averted by the policy reform. The reform adjusted the market and made insurance outcomes better, highlighting the potential importance of corrective regulation in such contexts. However, because the reform led to lower coverage, it may have negative welfare implications for consumers. Second, this paper provides an indirect evaluation of a policy that restrict "buying on credit". Purchasing arrangements to pay later boost retail trade in many developing countries (IMF 2012). But the ability to buy insurance on credit can yield large and economically substantial moral hazard effects in the market. Finally, estimated gains from the policy via reduction in moral hazard may extend to the functioning of markets in other settings.

This paper provides a first step in understanding the impacts of buying insurance on credit and the potential role of credit constraints for moral hazard. Ongoing research embodies four extensions of it. First, governments and regulators across other countries have either adopted a similar "no premium, no cover" reform or considering its adoption. I aim to consider the implications of the proposed approach and findings in other developing countries that currently have such insurance reforms in force: Nigeria and Gambia. The underlying legal and financial institutions are different, which may well matter for the functioning of the existing insurance markets and enforcement of contracts. Evidence from these varying contexts will therefore provide additional external validity and a further evaluation of the growing insurance policies, including the impacts on firms' balance sheets, potential market fraud and re-insurance behavior.

Second, consumers might have reduced their driving speed in response to this insurance regulation since coverage and the occurrence of losses were reduced. I aim to examine the co-impacts of the policy on local air quality, appealing to the literature on the effects of regulation on air pollution (Greenstone 2004; Davis 2008). I have done some preliminary analysis suggesting modest reductions in air pollution as measured by particulate matter

at the policy cutoff. Next, the results show that moral hazard is largest among the credit constrained customers, but that link was non-monotonic. I aim to explore the nonlinear link between liquidity constraints and moral hazard effects, as this could have important implications for the design of contracts and policies to alleviate moral hazard. Finally, I plan to investigate whether interlinking credit with insurance markets can induce adverse selection, and the implied welfare implications. There are indications from preliminary analysis that consumers who bought insurance on credit signal as bad risk-types, as compared to their counterparts who paid contracts upfront.

References

[1] Banerjee, Abhijit. 2001. "Contracting Constraints, Credit Markets and Economic Development." in M. Dewatripont, L. P. Hansen and S. J. Turnovsky (eds.) *Advances in Economics and Econometrics*, Cambridge: Cambridge University Press.

[2] Banerjee, Abhijit and Esther Duflo. 2011. "Poor Economic: A Radical Rethinking of the Way to Fight Global Poverty. New York: PublicAffairs." 15th Edition. http://onlinelibrary.wiley.com/doi/10.1002/jid.2936/abstract

[3] Banerjee, Abhijit, Esther Duflo, and Richard Hornbeck. 2014. "Bundling Health Insurance and Microfinance in India: There Cannot Be Adverse Selection If There Is No Demand." *American Economic Review* 104(5): 291-97.

[4] Bardhan, Pranab K. 1980. "Interlocking Factor Markets and Agrarian Development: A Review of Issues." *Oxford Economic Papers* 32(1): 82-98.

[5] Bardhan, Pranab K. 1989. The Economic Theory of Agrarian Institutions: Clarendon Press Oxford.

[6] Bell, Clive. 1988. "Credit Markets and Interlinked Transactions." In *Handbook of Development Economics*. eds. by Hollis Chenery, and T.N. Srinivasan, 1 of Handbook of Development Economics: Elsevier, Chap. 16 763-830.

[7] Blundell, Richard W., and James L. Powell. 2003. "Endogeneity in Nonparametric and Semiparametric Regression Models." in M. Dewatripont, L. P. Hansen and S. J. Turnovsky (eds.) *Advances in Economics and Econometrics*, Cambridge: Cambridge University Press.

[8] Braverman, Avishay, and Joseph E. Stiglitz. 1982. "Sharecropping and the Interlinking of Agrarian Markets." *American Economic Review*, 72 (4): 695-715.

[9] Braverman, Avishay, and Joseph E. Stiglitz. 1986. "Landlords, Tenants and Technological Innovations." *Journal of Development Economic*s, 23: 383-413.

[10] Casaburi, Lorenzo, and Jack Willis. 2017. "Time vs. State in Insurance: Experimental Evidence from Contract Farming in Kenya." Mimeo, Harvard University.

[11] Carter, Michael R, Lan Cheng, and Alexander Sarris. 2013. "The impact of Interlinked Index Insurance and Credit Contracts on Financial Market Deepening and Small Farm Productivity." Mimeo, University of California, Davis.

[12] Chetty, Raj. 2008. "Moral Hazard versus Liquidity and Optimal Unemployment Insurance." *Journal of Political Economy* 116(2): 173–234.

[13] Chiappori, Pierre-André, and Bernard Salanié. 2000. "Testing for Asymmetric Information in Insurance Markets." *Journal of Political Economy* 108(1): 56–78.

[14] Chiappori, Pierre-André, and Bernard Salanié. 2014. "Asymmetric Information in Insurance Markets: Predictions and Tests." in G. Dionne (ed.) *Handbook of Insurance*, 2nd edition.

[15] Chiappori, Pierre-André, Bruno Jullien, Bernard Salanié and François Salanié. 2006. "Asymmetric Information in Insurance: General Testable Implications." *Rand Journal of Economics* 37(4): 783–798.

[16] Cole, Shawn, Xavier Gine, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery. 2013. "Barriers to Household Risk Management: Evidence from India." *American Economic Journal: Applied Economics*, 5(1): 104–35.

[17] Cohen, Alma, and Liran Einav. 2007. "Estimating Risk Preferences from Deductible Choice." *American Economic Review* 97(3): 745–88.

[18] Cohen, Alma, and Rajeev Dehejia. 2004. "The Effect of Automobile Insurance and Accident Liability Laws on Traffic Fatalities." *Journal of Law and Economics* 47(2): 357–393.

[19] Cohen, Jessica, and Pascaline Dupas. 2010. "Free Distribution or Cost-Sharing? Evidence from a Randomized Malaria Prevention Experiment." *Quarterly Journal of Economics* 125(1): 1–45.

[20] Davidoff, Thomas, and Gerd Welke. 2007. "Selection and Moral Hazard in the Reverse Mortgage Market." Mimeo, University of British Columbia.

[21] Davis, W. Lukas. 2008. "The Effect of Driving Restrictions on Air Quality in Mexico City." *Journal of Political Economy* 116(1): 38–81.

[22] Deaton, Angus. 1991. "Saving and Liquidity Constraints." *Econometrica* 59(5): 1221–1248.

[23] Dynarski, M. Susan. "Does Aid Matter? Measuring the Effect of Student Aid on College Attendance and Completion." *American Economic Review* 93(1): 297–288.

[24] Einav, Liran, and Amy Finkelstein. 2011. "Selection in Insurance Markets: Theory and Empirics in Pictures." *Journal of Economic Perspectives* 25(1): 115–138.

[25] Einav, Liran, Amy Finkelstein, and Jonathan Levin. 2010. "Beyond Testing: Empirical Models of Insurance Markets." *Annual Review of Economics* 2: 311–36.

[26] Einav, Liran, Amy Finkelstein, Stephen P. Ryan, Paul Schrimpf, and Mark R. Cullen. 2013. "Selection on Moral Hazard in Health Insurance." *American Economic Review* 103(1): 178–219.

[27] Escanciano, Juan C., Bernard Salanié, and Nesse Yildiz. 2016. "Testing for Moral Hazard When Adverse Selection is Present." Mimeo, Columbia University.

[28] Fang, Hanming, Michael Keane, and Dan Silverman. 2008. "Sources of Advantageous Selection: Evidence from the Medigap Insurance Market." *Journal of Political Economy* 116(2): 303–350.

[29] Finkelstein, Amy, and Kathleen McGarry. 2006. "Private Information and Its Effect on Market Equilibrium: New Evidence from Long-term Care Insurance." *American Economic Review* 96(4): 938–958.

[30] Finkelstein, Amy, and James Poterba. 2002. "Selection Effects in the Market for Individual Annuities: New Evidence from the United Kingdom." *Economic Journal* 112(476): 28–50.

[31] Gerfin, Michael and Martin Schellhorn. 2006. "Nonparametric Bounds on the Effect of Deductibles in Health Care Insurance on Doctor Visits–Swiss Evidence." *Health Economics* 15 (9):1011–1020.

[32] Ghana Statistical Service (GSS). 2014. "Ghana Living Standards Survey Round 6" Main Report, GSS Publications.

[33] Ghosh, Parikshit, Dilip Mookherjee, and Debraj Ray. 2000. "Credit Rationing in Developing Countries: An Overview of the Theory." in Dilip Mookherjee and Debraj Ray (eds.) *A Reader in Development Economics*, London: Blackwell.

[34] Gine, Xavier and Dean Yang. 2009. "Insurance, Credit, and Technology Adoption: Field Experimental Evidence from Malawi." *Journal of Development Economics* 89(1): 1-11.

[35] Greenstone, Michael. 2004. "Did the Clean Air Act cause the Remarkable Decline in Sulfur Dioxide Concentrations?" *Journal of Environmental Economics and Management* 47(3): 585–611.

[36] Gross, Tal, Matthew J. Notowidigdo, and Jialan Wang. 2014. "Liquidity Constraints and Consumer Bankruptcy: Evidence from Tax Rebates." *Review of Economics and Statistics* 96(3): 431–443.

[37] Hansman, Christopher. 2017. "Asymmetric Information and the Link Between Leverage and Mortgage Default." Mimeo, Columbia University.

[38] Hendren, Nathaniel. 2013. "Private Information and Insurance Rejections." *Econometrica* 81(5): 1713–176.

[39] Holmstrom, Bengt. 1979. "Moral Hazard and Observability." *Bell Journal of Economics* 10(1): 74–91.

[40] Imbens, Guido W., and Thomas Lemieux. 2008. "Regression Discontinuity Designs: A Guide to Practice." *Journal of Econometrics* 142 (2): 615–635.

[41] International Monetary Fund (IMF). 2012. "Brazil: 2012 Article IV Consultation: Staff Report; Public Information Notice on the Executive Board Discussion; and Statement by the Executive Director for Brazil." Accessed July 25, 2016. https://www.imf.org/external/pubs/cat/longres.aspx?sk=26086.0

[42] Karlan, Dean, Robert Osei, Isaac Osei-Akoto, and Christopher Udry. 2014. "Agricultural Decisions after Relaxing Credit and Risk Constraints." *Quarterly Journal of Economics* 129(2): 597–652.

[43] Kim, Meeroo. 2017. "Multidimensional Heterogeneity in the Consumer Credit Market." Mimeo, Columbia University.

[44] Krueger, Alan B., and Bruce D. Meyer. 2002. "Labor Supply Effects of Social Insurance," in Alan J. Auerbach and Martin S Feldstein, (eds.), *Handbook of Public Economics*, pp. 2327–2392. Amsterdam and New York: Elsevier.

[45] Lee, David S. 2002. "Trimming for Bounds on Treatment Effects with Missing Outcomes." National Bureau of Economic Research Research Working Paper 277.

[46] Lee, David S., and Thomas Lemieux. 2010. "Regression Discontinuity Designs in Economics." *Journal of Economic Literature* 48(1): 281–255.

[47] Lee, Jeong-Joon, and Yasuyuki Sawada. 2010. "Precautionary Saving under Liquidity Constraints: Evidence from Rural Pakistan." *Journal of Development Economics* 91(1): 77–86.

[48] Liu, Yanyan, Kevin Chen, Ruth Hill, and Chengwei Xiao. 2016. "Delayed Premium Payment, Insurance Adoption, and Household Investment in Rural China." IFPRI Discussion Paper (01306).

[49] Manski, Charles F. 1990. "Nonparametric Bounds on Treatment Effects." *American Economic Review* 80(2): 319–323.

[50] Manski, Charles F. 1997. "Monotone Treatment Response." *Econometrica* 65(6): 1311–1334.

[51] Manski, Charles F., and John Pepper V. 2000. "Monotone Instrumental Variables: With an Application to the Returns to Schooling." *Econometrica* 68(4): 997–1010.

[52] National Insurance Commission (NIC). 2011. "Annual Report" Ghana, NIC Publications.

[53] National Insurance Commission (NIC). 2015. "About NIC." Accessed February 7, 2015. http://www.nicgh.org/live/en/

[54] Rothschild, Michael and Joseph Stiglitz. 1976. "Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information." *Quarterly Journal of Economics* 90(4): 629–649.

[55] Salanié, Bernard. 2005. "The Economics of Contracts: A Primer." 2nd Edition. MIT Press.

[56] Schneider, Henry S. 2010. "Moral Hazard in Leasing Contracts: Evidence from the New York City Taxi Industry" *Journal of Law and Economics* 53(4): 783–805.

[57] Townsend, Robert M. 1979. "Optimal Contracts and Competitive Markets with Costly State Verification." *Journal of Economic Theory* 21(2): 265–293.

Table 1: **Transition Matrix: debtors vs switchers** [%]

| | | Before Policy | |
		DEBTOR=0	DEBTOR=1
After Policy	SWITCHER=0	99.98	0.57
	SWITCHER=1	0.02	**99.43**
		100	100

Notes: Debtors are consumers who were buying insurance on credit before the policy reform. Switchers are consumers who moved from Comprehensive to Basic contracts after policy reform. Over 99% of people who purchased insurance on credit switched to contracts with lower coverage.

Table 2: **Formal "moral hazard tests"**

Formal Test	LOSS		CLAIMS	
	Statistic /Estimate	*Prob. value*	*Statistic /Estimate*	*Prob. value*
Proposed L_2-Type	-	-	0.167	0.040
Kolmogorov–Smirnov	-	-	0.113	0.001
OLS	[0.016]	0.001	[2.848]	0.038

Notes: Table reports the test statistics and p-values for the two nonparametric tests: Proposed L_2-Type and Kolmogorov–Smirnov. The last row of the Table reports parameter estimates, contained in square brackets, and p-values from OLS estimations separately for loss, and claims outcomes. The p-value for the Proposed L_2-Type test are based on 999 nonparametric bootstrap resamples of the test statistic.

Table 3: **Estimates: Bounds on moral hazard**

LOSS				CLAIMS		
	Bounds	95% CI			Bounds	95% CI
lb	0.0089	[0.0013, 0.015]		*lb*	51.96	[10.70, 117.45]
ub	0.7775	[0.7647, 0.7858]		*ub*	108172.02	[107224.49, 109509.68]

Notes: Table reports both the lower and upper bound estimates on moral hazard separately for loss, and claims outcomes. CI denotes confidence interval. lb and ub denotes lower and upper bound on moral hazard. The 95% confidence intervals are based on 999 nonparametric bootstrap resamples for the various objects of interest.

Table 4: **Naive estimates: lower bound** Δ^l

OUTCOME	Bounds	95% CI	Selection Effect
LOSS	0.035	[0.0075, 0.082]	0.026
CLAIMS	381.70	[25.15, 782.89]	329.70

Notes: Table reports "naive" lower bound estimates on moral hazard separately for loss, and claims outcomes. Estimations are based on a naive lower bound estimator that neglects adverse selection. CI denotes confidence interval. lb denotes lower bound on moral hazard. The 95% confidence intervals are based on 999 nonparametric bootstrap resamples for the various objects of interest.

Table 5: **ESTIMATES: CUSTOMERS BELOW VS ABOVE MEDIAN PROBABILITY**

Customers	CLAIMS		LOSS	
	–Bounds–	95% CI	–Bounds–	95% CI
Below Median $< P(c^r;x)_{[50]}$	lb 16.47	[1.90,59.53]	lb 0.0043	[0.0002,0.0302]
Above Median $\geq P(c^r;x)_{[50]}$	lb 80.32	[17.03,140.21]	lb 0.0073	[0.0004,0.0208]

Notes: Table reports the lower bound estimates on moral hazard for customers below and above the median of the predicted credit probability (see Figures 5a and 5b), denoted $P(c^r;x)_{[50]}$. CI denotes confidence interval. lb denotes lower bound on moral hazard. The 95% confidence intervals are based on 999 nonparametric bootstrap resamples for the various objects of interest. The median is $\cong 0.075$.

Table 6: **ESTIMATES: BOUNDS ON MORAL HAZARD BY CREDIT QUARTILES**

	CLAIMS		LOSS	
Quartile	–Bounds–	95% CI	–Bounds–	95% CI
q1	lb 30.04	[10.98,57.72]	lb 0.0121	[0.0021,0.0260]
q2	lb 16.38	[3.22,24.24]	lb 0.0028	[0.0002,0.0077]
q3	lb 190.90	[22.23,361.28]	lb 0.0662	[0.0003,0.0701]
q4	lb 45.66	[5.45,135.38]	lb 0.0029	[0.0001,0.0105]

Notes: Table reports the lower bound estimates on moral hazard by quartiles of predicted credit probabilities (see Figures 5a and 5b). CI denotes confidence interval. lb denotes lower bound on moral hazard. q_1, q_2, q_3 and q_4 correspond to the first, second, third and fourth quartiles of credit probabilities respectively. The 95% confidence intervals are based on 999 nonparametric bootstrap resamples for the various objects of interest. These quartile categories are useful in describing the distribution of constraints in credit and providing enough observations in each category to ensure that estimations are not done on completely empty cells. In practice, I create the respective quartile categories as follows: $[min, P(c^r;x)_{[25]}]$, $(P(c^r;x)_{[25]}, P(c^r;x)_{[50]}]$, $(P(c^r;x)_{[50]}, P(c^r;x)_{[75]}]$ and $(P(c^r;x)_{[75]}, max]$ where min denotes minimum, max denotes maximum, and the numbers in squared brackets represent the 25th, 50th/median, and 75th percentile values. $min = 3.74E - 06$; $P(c^r;x)_{[25]} = 0.046$; $P(c^r;x)_{[50]} = 0.075$; $P(c^r;x)_{[75]} = 0.131$ and $max = 0.403$.

Table 7: **Effect of reform on differential pricing**

DV: **Premiums**	(1)	(2)	(3)
D_{it}		225.9 (503.0)	-292.5 (305.9)
Policy$_t$	18.67(15.58)	-85.77 (149.9)	33.78 (72.79)
$D_{it} \times$ Policy$_t$		206.4 (162.0)	-111.4 (78.74)
NCD level			-55.78** (23.12)
Loading			3.844*** (0.0495)
Year of manuf.			75.25*** (10.14)
Seat capacity			-16.64** (7.097)
Cert. Type dummies	No	No	Yes
Constant	428.1***(11.46)	1,673***(400.3)	-149,535***(20,336)
R-squared	<0.01	<0.01	0.77
Agent-level FEs	Yes	Yes	Yes

Notes: Table reports results from the regression of premiums on policy reform and contract choice variables. Errors are robust to arbitrary correlations and heteroskedasticity, and are shown in parentheses. *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Table 8: **SAME POLICY NUMBERS: BOUNDS ON MORAL HAZARD**

CLAIMS		LOSS	
Lower bound	95% CI	Lower bound	95% CI
33.21	[9.02, 55.44]	0.0061	[0.0001, 0.0124]

Notes: Table reports the lower bound estimates on moral hazard separately for loss, and claims outcomes. The results are shown for the set of customers with same policy numbers before and after the policy reform, April 1, 2014. CI denotes confidence interval. The 95% confidence intervals are based on 999 nonparametric bootstrap resamples for the various objects of interest. Estimate 33.21 translates to about 41.0% of mean claim amounts.

Table 9: **SAME POLICY NUMBERS: CUSTOMERS BELOW VS ABOVE MEDIAN PROBABILITY**

Customers	CLAIMS		LOSS	
	–Bounds–	95% CI	–Bounds–	95% CI
Below: $< P(c^r;x)_{[50]}$	lb 42.84	[0.21,168.47]	lb 0.0125	[0.0006,0.0411]
Above: $\geq P(c^r;x)_{[50]}$	lb 107.34	[26.65,661.66]	lb 0.0172	[0.0019,0.0397]

Notes: Table reports the lower bound estimates on moral hazard for customers below (unconstrained) and above (constrained) the median of the predicted credit probabilities, denoted $P(c^r;x)_{[50]}$. The estimates are based on the set of customers with the same policy numbers before and after the reform's introduction, April 1, 2014. CI denotes confidence interval. lb denotes lower bound on moral hazard. The 95% confidence intervals are based on 999 nonparametric bootstrap resamples for the various objects of interest. The median is $\cong 0.075$.

Table 10: **ONLY LIABILITY EVENTS UNDER BOTH CONTRACTS: BOUNDS ON MORAL HAZARD**

CLAIMS			**LOSS**	
Lower bound	95% CI		Lower bound	95% CI
31.62	[3.92, 47.83]		0.0068	[0.0001, 0.0118]

Notes: Table reports the lower bound estimates on moral hazard separately for loss, and claims outcomes. The results are shown for only liability events: covered under both comprehensive and third-party liability contracts. CI denotes confidence interval. The 95% confidence intervals are based on 999 nonparametric bootstrap resamples for the various objects of interest. The estimate 31.63 translates to 39.10% of mean claim amounts; 0.0068 translates to about 16.58% of loss occurrence probabilities or the number of claims.

Table 11: **Bounds on moral hazard for different time windows**

Window	**CLAIMS**		**LOSS**	
	Lower bounds	95% CI	Lower bounds	95% CI
8 Months	32.30	[0.13, 68.80]	0.0058	[0.0001, 0.0101]
4 Months	41.50	[5.76, 94.96]	0.0049	[0.0001, 0.0212]

Notes: Table reports the lower bound estimates on moral hazard separately for loss and claims outcomes. The results are shown for different time windows around the date of the policy reform, April 1, 2017. CI denotes confidence interval. The 95% confidence intervals are based on 999 nonparametric bootstrap resamples for the various objects of interest. Estimates (32.30 and 41.50) translate is about (34.0% and 41.0%) of mean claim amounts.

Table 12: **WINSORIZED DATA: BOUNDS ON MORAL HAZARD**

	CLAIMS		LOSS	
	Lower bound	95% CI	Lower bound	95% CI
95% Winsorization	35.12	[1.50, 65.53]	0.0078	[0.0045,0.0135]

Notes: Table reports the lower bound estimates on moral hazard separately for loss, and claims outcomes. Data 95% winsorized by replacing all data below the 2.5th percentile with the 2.5th percentile, and data above the 97.5th percentile with the 97.5th percentile value. For bounds estimation, these percentile values are 0 and 12976, respectively. CI denotes confidence interval. The 95% confidence intervals are based on 999 nonparametric bootstrap resamples for the various objects of interest. Estimate 35.12 translates to about 41.2% of mean claim amounts.

Table 13: **CERTAINTY EQUIVALENT LOSS VS. PROFIT GAINS FROM NO-CREDIT POLICY**

△**CERTAINTY EQUIVALENT**		△**PROFIT**	
Absolute risk aversion,γ	$\triangle CE$ (GHC)	Status: premium-debts	$\triangle \pi$ (GHC)
0.001	-111,559	All paid, pre-policy	1,023,168
0.003	-178,341	79% paid, pre-policy	2,048,883
		Never paid, pre-policy	9,210325

Notes: Table presents estimates for the certainty equivalent loss and gain in profits as a result of the no-credit policy. Left panel gives the estimates for certainty equivalent loss for different absolute risk aversion parameters. To be more conservative, I allow for a larger value of $\gamma = 0.003$ (more value for insurance) and only present results for the case where the share of consumers who credit insurance premiums "never paid" before the policy reform (more value for buying on credit to consumers; less enforcement of credit arrangements). Right panel gives the profit gains under different assumptions regarding the enforcement of credit arrangements (i.e., repayment of premium debts) prior to the policy reform. As shown in Section 2.3, the repayment rate for premium debts is about 79%.

69

Figure 1: **Channels for selling policies**
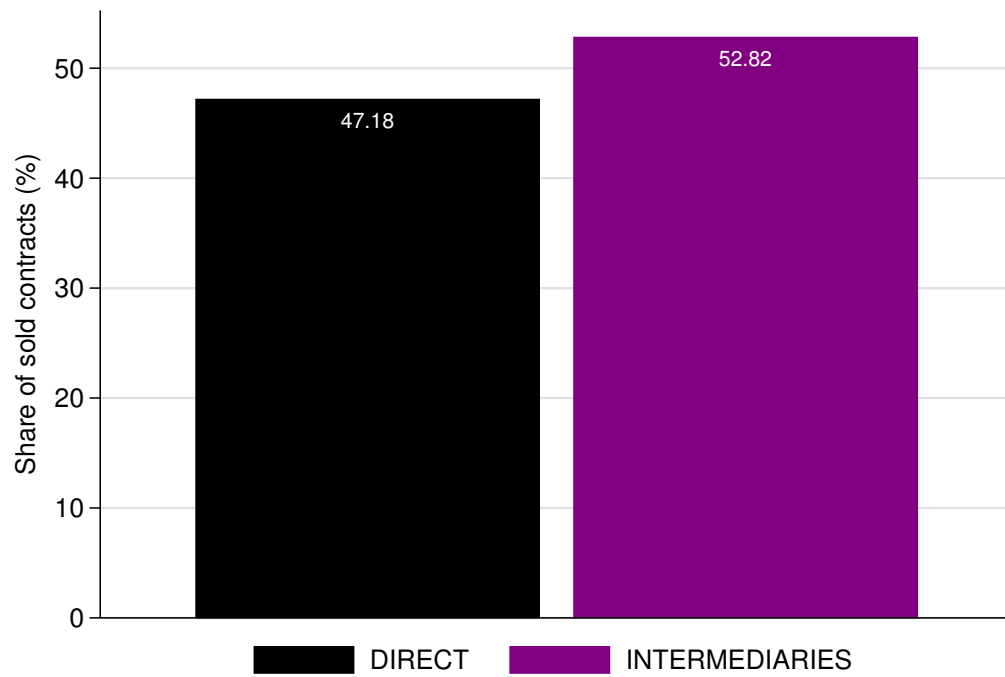
Note: The intermediaries category include insurance brokers and agents

Notes: Figure shows the different channels that insurance policies are sold. Many insurance contracts are acquired through agency channels: market intermediaries.

Figure 2: CREDIT TAKE-UP OVER TIME

NOTES: (1) Intercept = 0.27 & (2) Raw Data

(a) PROBIT REGRESSION OF TAKE-UP STATUS
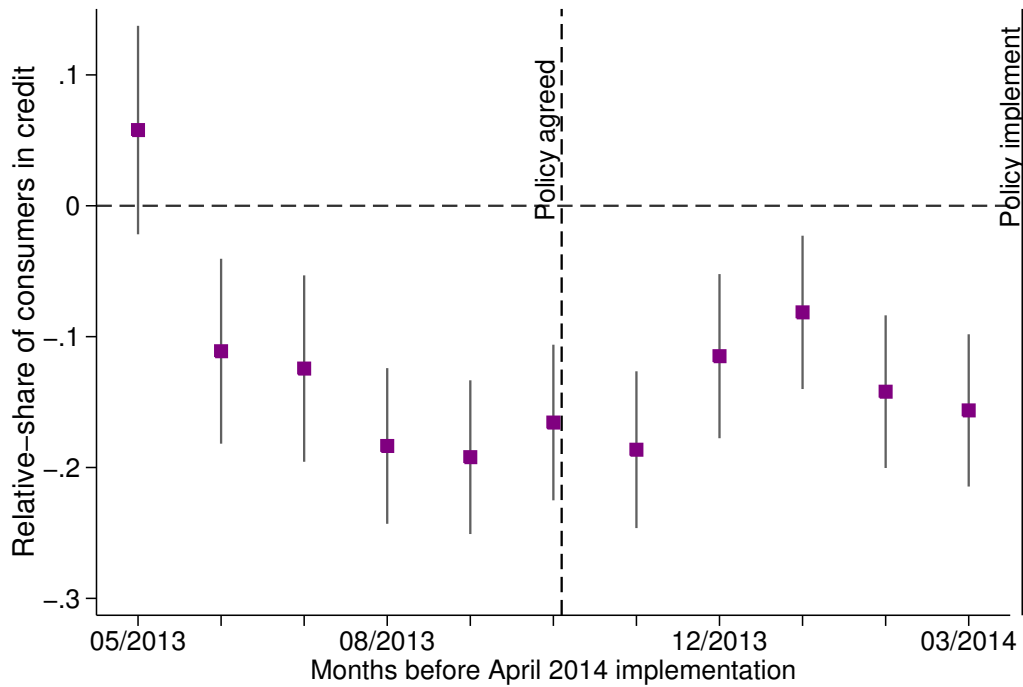
NOTES: (1) Apr2013 = 0.22; (2) Controls for consumer observables
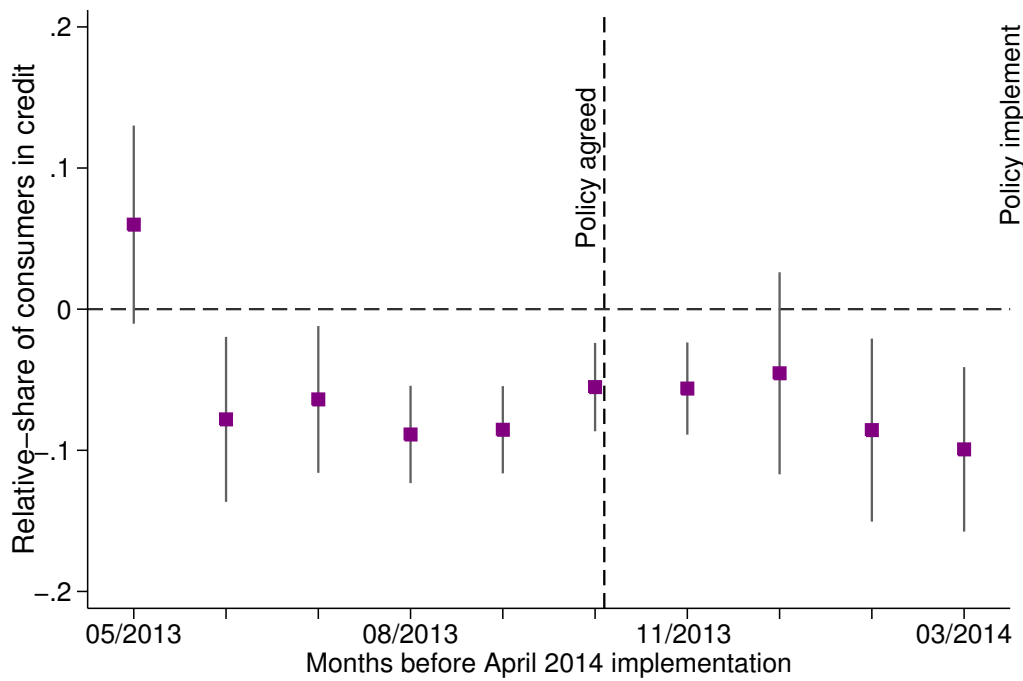
(b) PROBIT REGRESSION OF TAKE-UP STATUS WITH CONTROLS

Notes: Figure is based on a probit regression of an indicator for buying insurance on credit against monthly dummies, with and without controls for consumer characteristics. The month-by-month coefficients are displayed with the 95% confidence intervals. In both cases, vertical lines are used to indicate the timing of the regulation.

Figure 3: **DISTRIBUTION OF PREMIUM-DEBT**
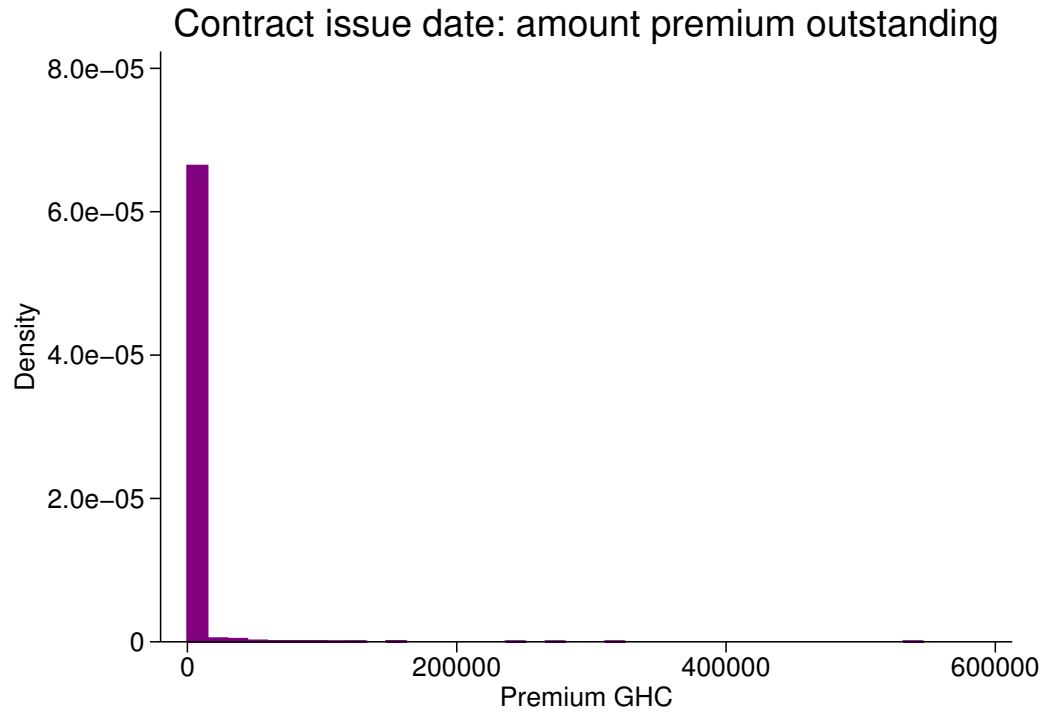
(a) **AMOUNT OWED (GHC)**
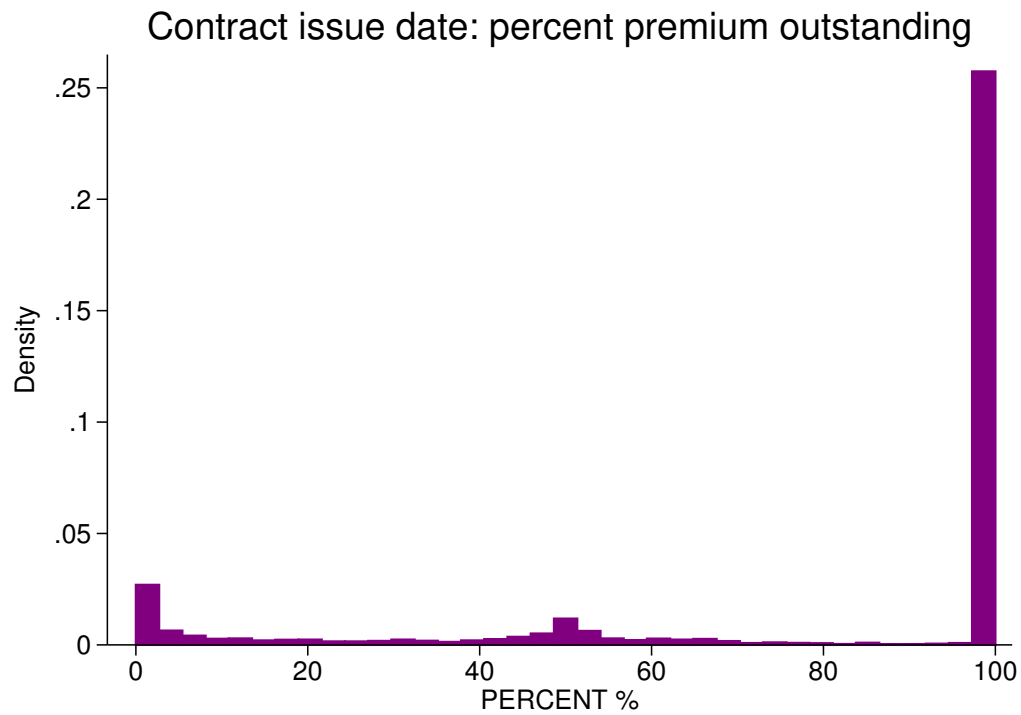
(b) **PERCENT OF PREMIUM IN DEBT**

Notes: Figure shows the distribution of outstanding premiums at the time contracts are signed. The amount of premium debt is shown in (a), maxing at GHC600000. In (b), the premium debt expressed a percentage of total premium is displayed. This ranges between 0.2% to 100%.

Figure 4: **DISTRIBUTION OF PREMIUM-DEBT BY SOURCE**
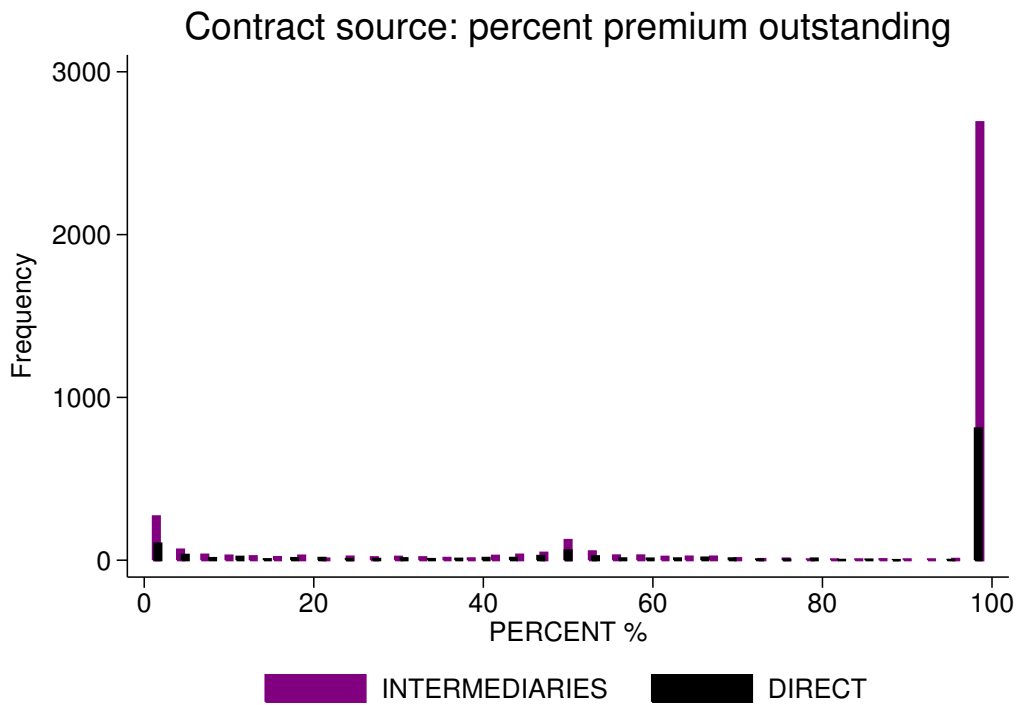
Notes: Figure shows the percent of outstanding premiums across the two channels of selling insurance policies: direct from the insurance firm versus intermediaries. The individual distributions are superimposed on each other. As shown, premium debts can range from 0.2% to 100% of premiums; many customers are more likely to initiate 100% premium debt contracts with intermediaries, compared to contracts from the insurer.

Figure 5: **Premium-debt repayment**
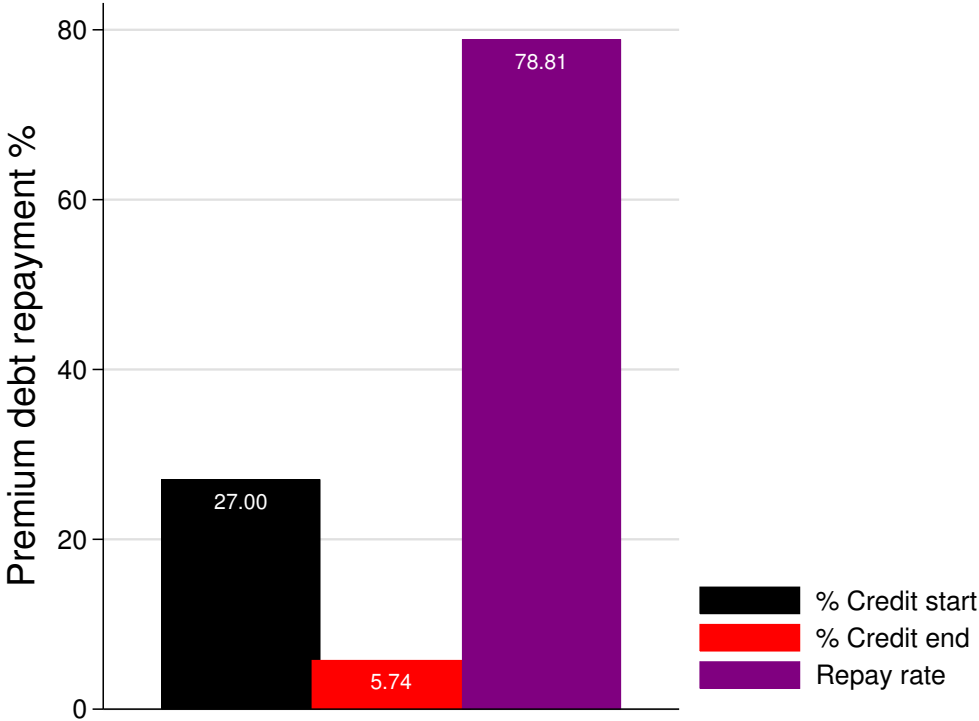
(a) **debt repayment before contract expires (extensive)**
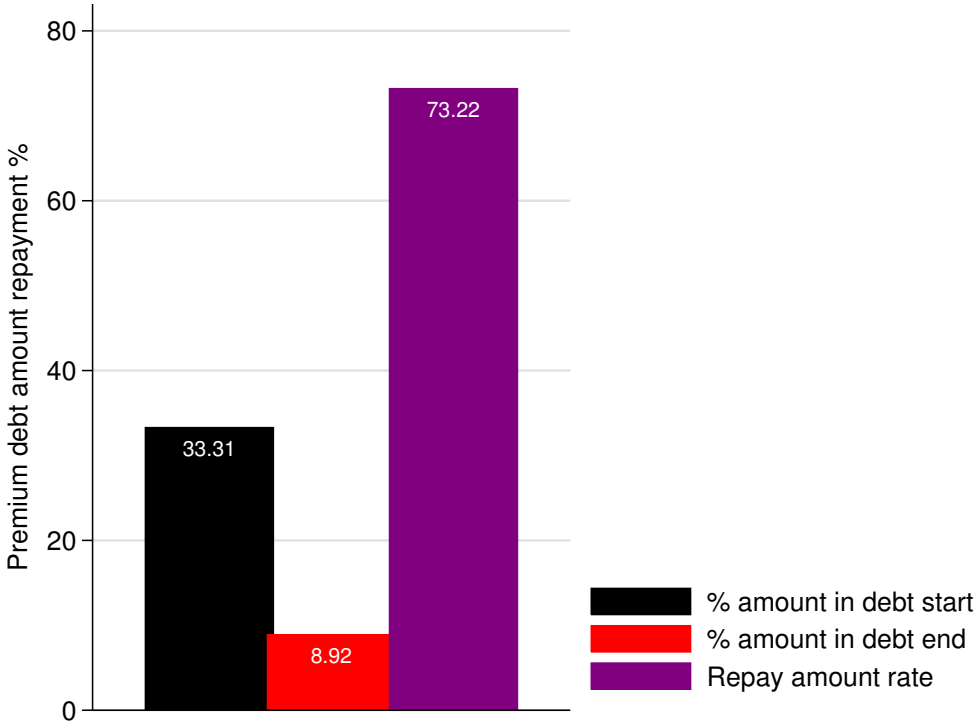
(b) **debt repayment before contract expires (intensive)**

74

Notes: Figures show the repayment rates for insurance premium debts prior to the no-credit policy. (a) Extensively: percent of consumers who began their contracts with credit and ended their coverage with/without some credit. (b) Intensively: percent of total premium amount in debt at the beginning of contracts versus the end of contracts prior to the reform.

Figure 6: **Choice probabilities conditional on reform**
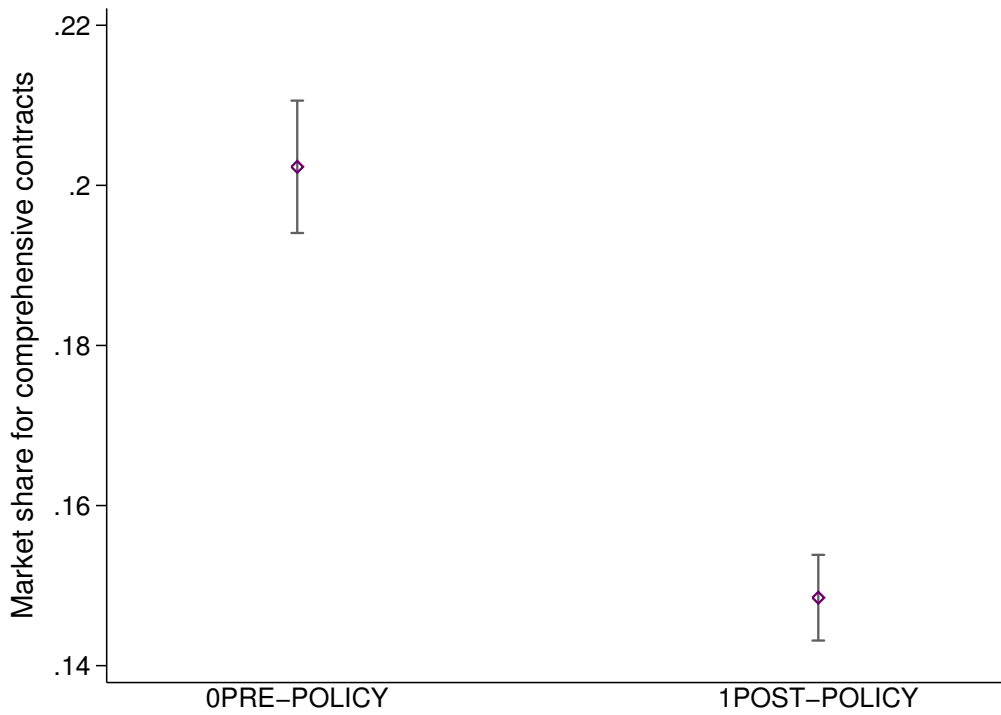
Notes: Figure shows the insurance choice probabilities for comprehensive contracts, before and after the regulatory reform. This is derived using the insurer's data set and a frequency estimator. The 95% confidence intervals are displayed around the estimates.

Figure 7: **Distribution at policy cutoff**

Year of vehicle manufacture around Policy date

NOTE: Conditional on contract space

(a) **age of vehicle**

Seat–capacity around Policy date
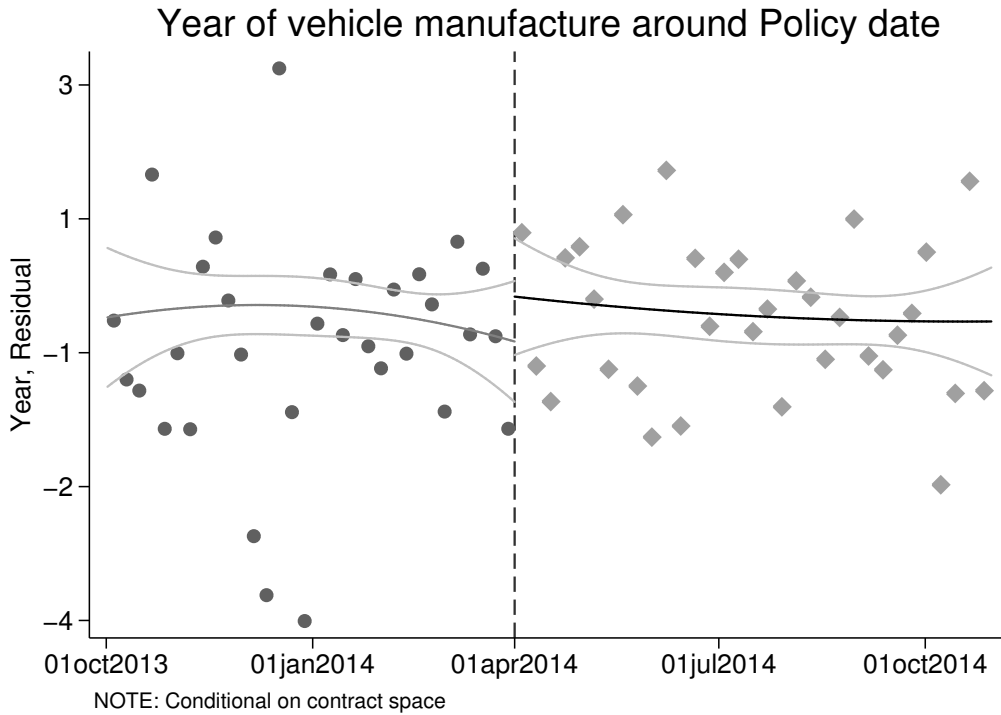
NOTE: Conditional on contract space
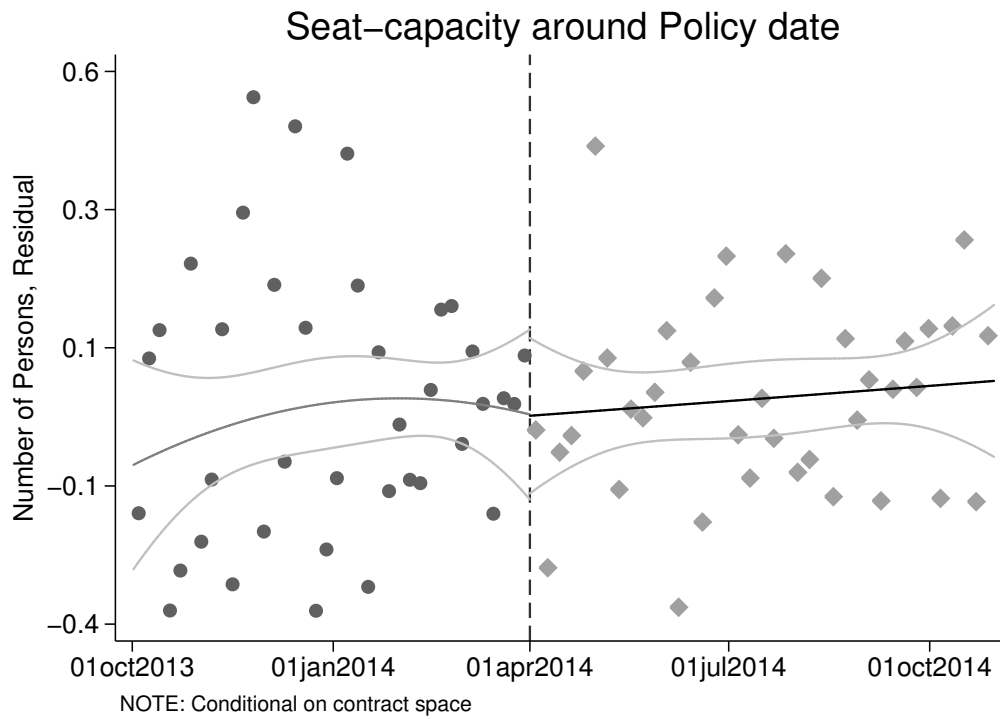
(b) **seat capacity of vehicle**

Notes: Figures display the distribution of the various customer characteristics (age of vehicles; seat capacity of vehicles) around the policy cutoff. In all cases, the 95% confidence intervals are displayed around the estimates.

Figure 8: **DISTRIBUTION AT POLICY CUTOFF**

Cubic capacity of vehicle around Policy date

NOTE: Conditional on contract space
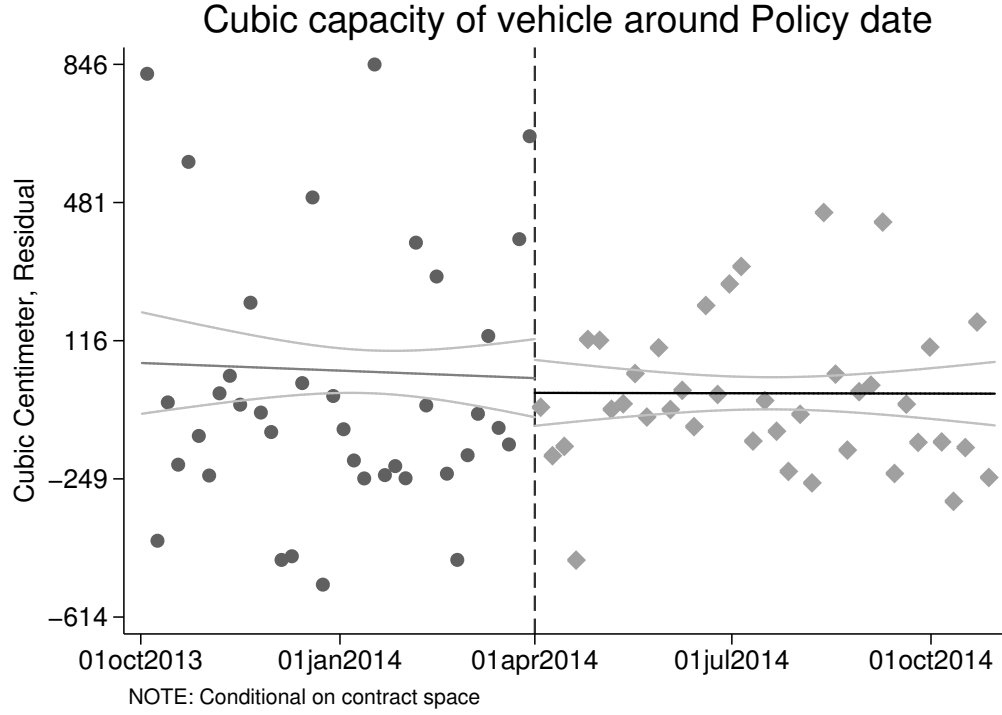
(a) **CUBIC CAPACITY OF VEHICLE**

	Private (%)	Commercial (%)
Pre-reform	88.44	11.56
Post-reform	88.49	11.51

Private includes: individual + corporate

(b) **POOL: SHARE OF PRIVATE VS BUSINESS-TYPE VEHICLES**

Notes: Figure shows the distribution of vehicles cubic capacity around the policy cutoff. The 95% confidence intervals are displayed around the estimates.

Figure 9: **Distribution at policy cutoff**

No−claim discounts around Policy date

NOTE: Conditional on contract space

(a) **no-claim discount**

Riskiness around Policy date

NOTE: Conditional on contract space
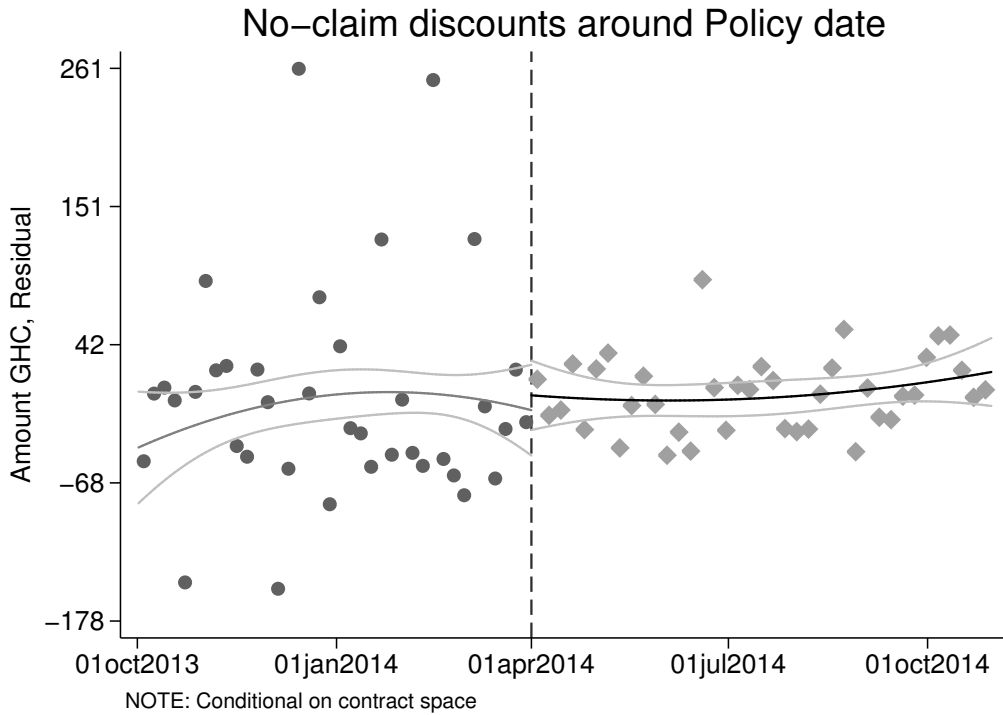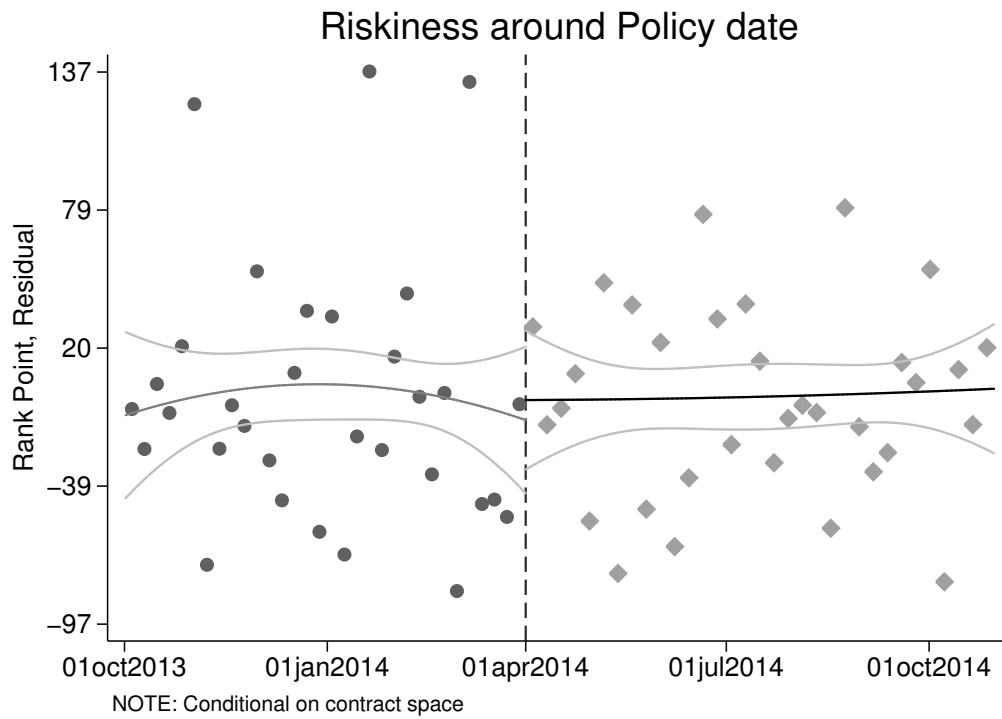
(b) **consumer riskiness score**

Notes: Figures show the distribution of the various customer characteristics (no-claim discount for premiums; riskiness scores) around the policy cutoff. In all cases, the 95% confidence intervals are displayed around the estimates.

Figure 10: **DISTRIBUTION OF CUSTOMERS CHARACTERISTICS**
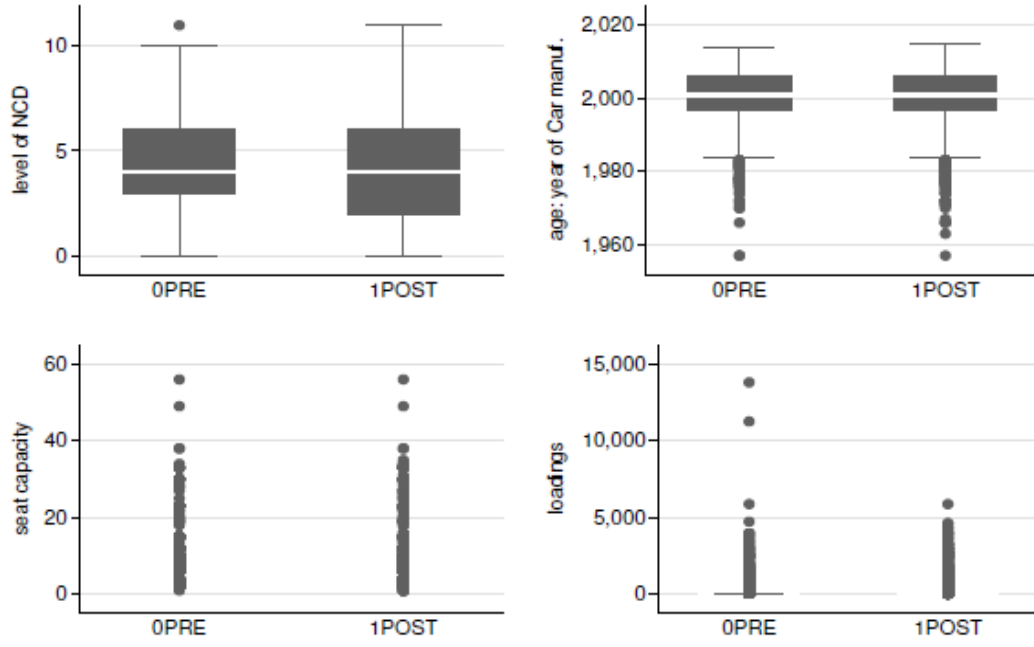
(a) DISTRIBUTIONS: $X|Z$
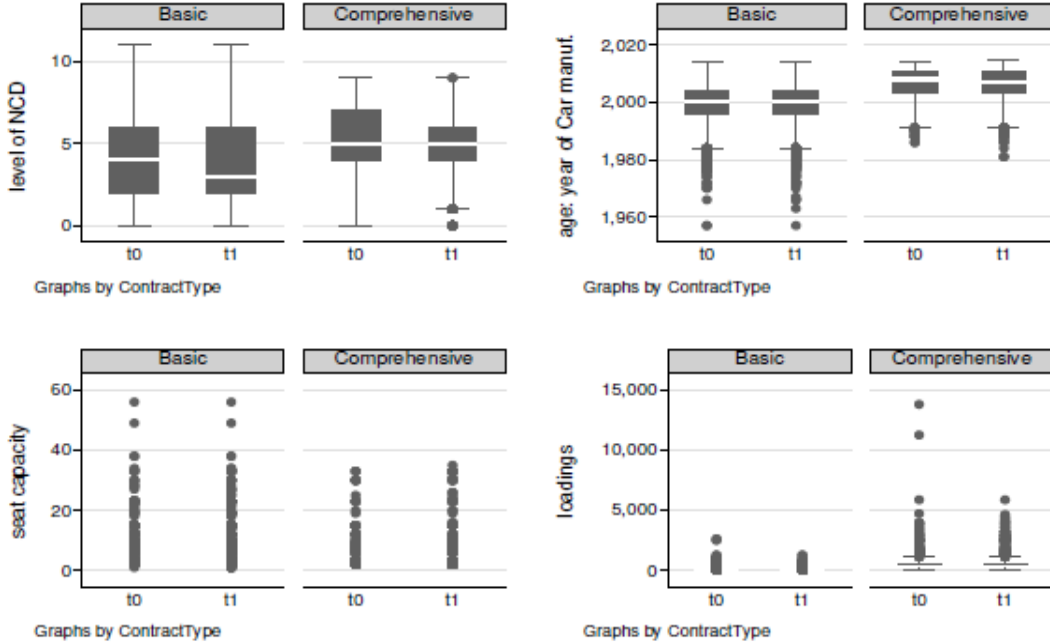
(b) DISTRIBUTIONS: $X|(Z, D)$

Notes: Figures display the distributions of customers characteristics conditional on time and choice of insurance contracts. (a)– similar distributions on observables across time t. (b)– similar distributions on observables within contracts.

Figure 11: **Distribution of claim amounts**$|Z$
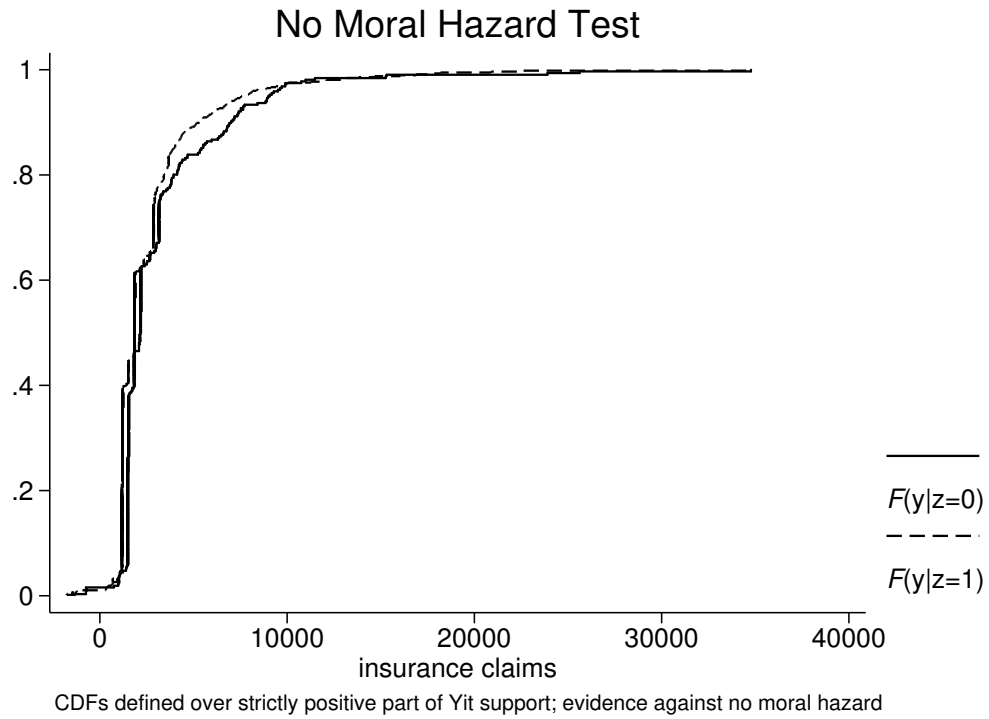
CDFs defined over strictly positive part of Yit support; evidence against no moral hazard

Notes: Figure shows the predicted distribution of claims before and after the no-credit regulation. The distribution in dash corresponds to realizations after the policy $z = 1$. The distributions reflect strictly positive claim amounts. The no-moral hazard test holds for any realization of y.

Figure 12: **DISTRIBUTION OF CLAIM AMOUNTS**
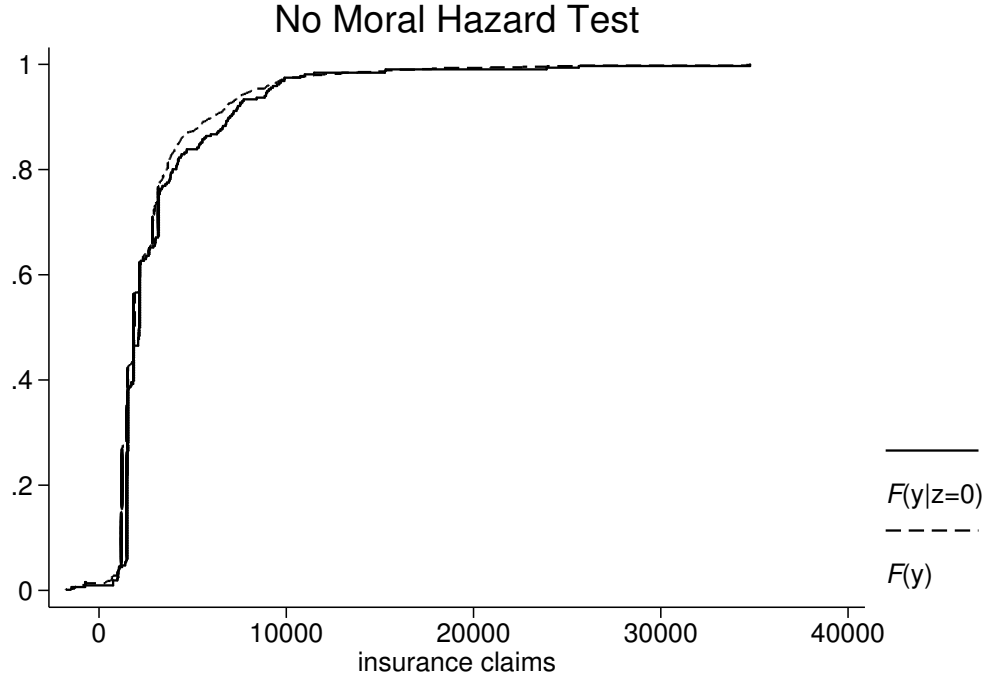
(a) **PRE-POLICY VS UNCONDITIONAL**:$\hat{F}(y|z=0)$ vs $\hat{F}(y)$
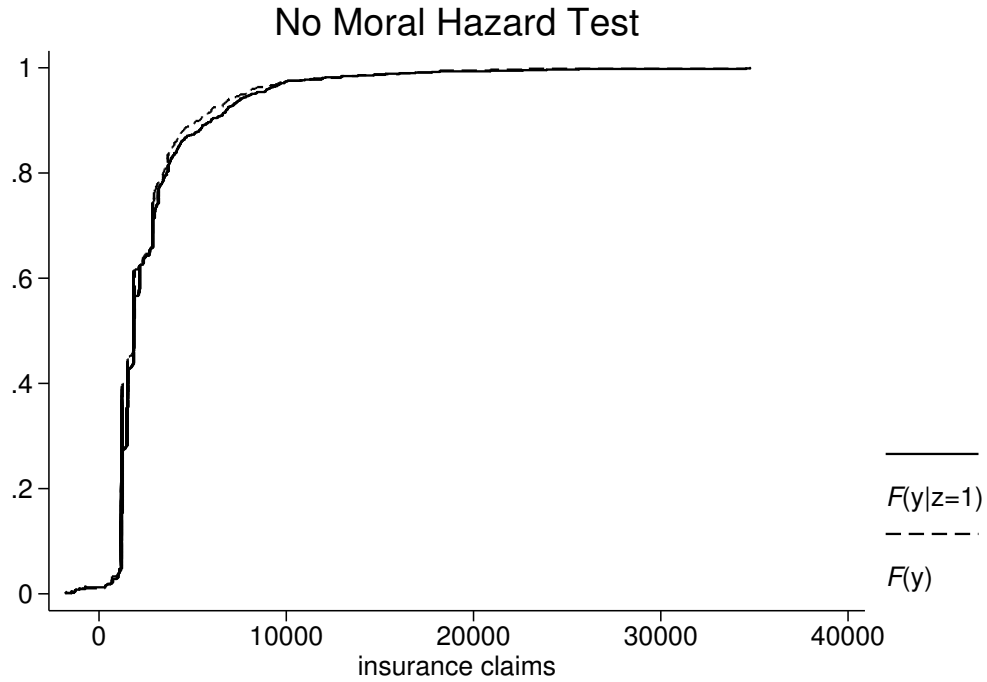
(b) **PSOT-POLICY VS UNCONDITIONAL**:$\hat{F}(y|z=1)$ vs $\hat{F}(y)$

Notes: Figures shows the predicted distribution of claims. In (a) the pre-policy ($z = 0$) outcomes are compared with the overall claims. In (b) the post-policy ($z = 0$) outcomes are compared with the overall claims. The distributions reflect strictly positive claim amounts. The no-moral hazard test holds for any realization of y.

Figure 13: **Type of claim events conditional on policy**

Claim Events Not Covered by [Liability] Basic Contract
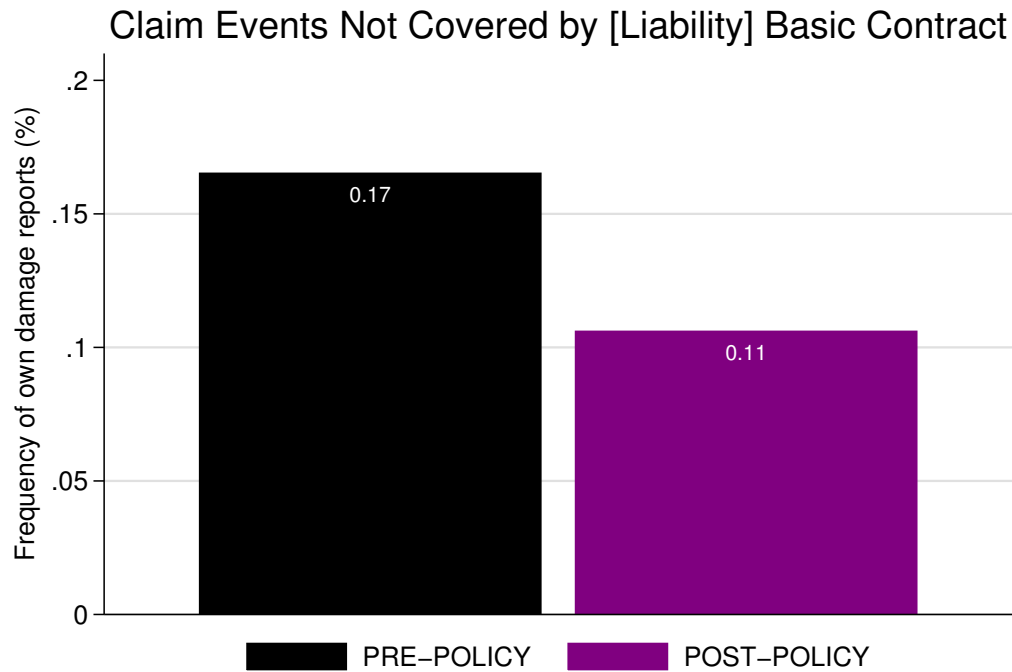
Note: Examples include crash to trees & partial theft of vehicle contents

(a) **events uncovered by basic contracts**

Claim Events Covered by Both Contracts
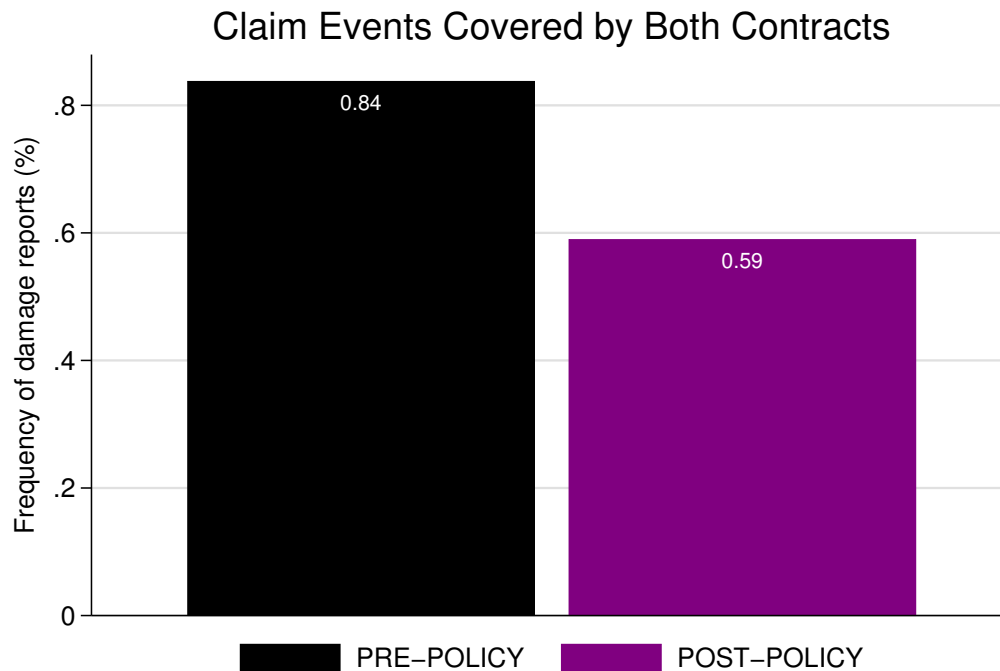
Note: Examples include third party injuries

(b) **events covered by both contracts**

Notes: Figures show the distribution of specific claim events before and after the policy reform. (a) shows the changes in the frequency of claim events that are not covered by basic contracts (i.e., covered by only comprehensive contracts). In (b), the distribution is shown for events that are covered by both contracts, which excludes the events in (a).

Figure 14: **CREDIT: PURCHASE PROBABILITIES**
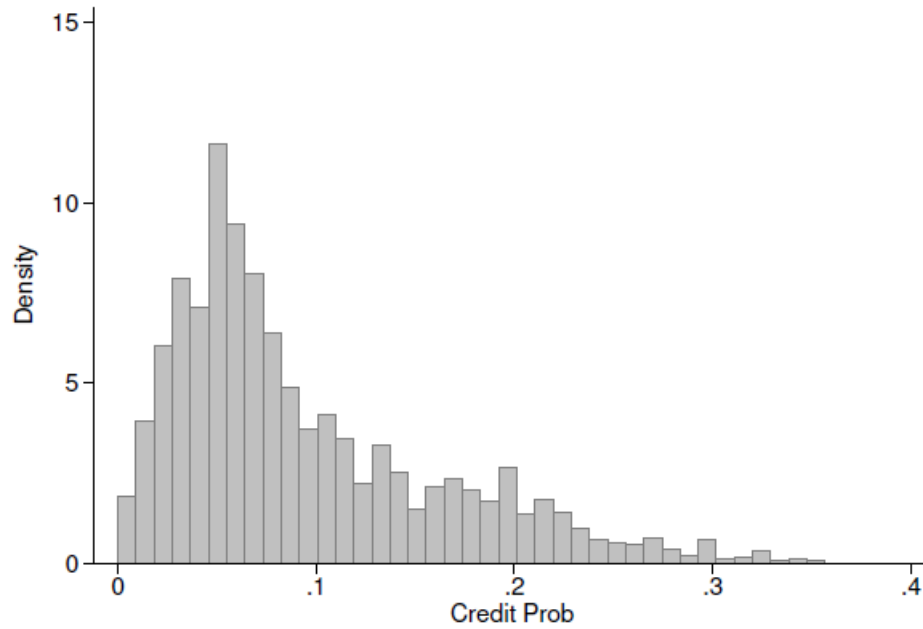
Note: Predicted credit distribution prior to National reform

(a) DISTRIBUTION OF CREDIT PROBABILITIES
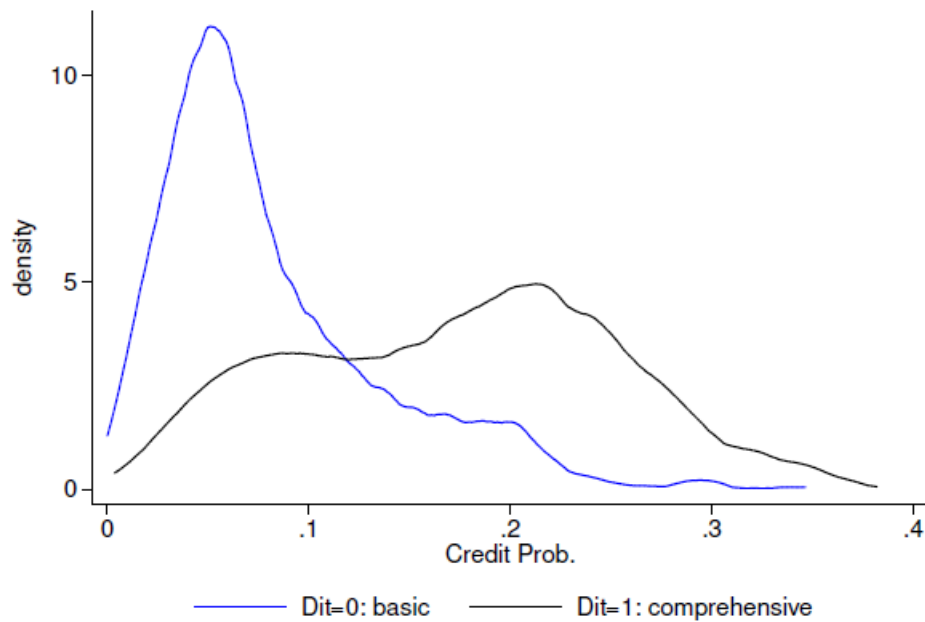
Note: Predicted credit distribution prior to reform by contract choice

(b) DISTRIBUTION OF CREDIT PROBABILITIES BY CONTRACT

Notes: Figures show the distribution of the estimated credit probabilities: ranging between 0-41%, exclusive. The overall distribution is displayed in (a). In (b), I condition this on the contract space. There is much higher probability of buying comprehensive contracts with credit, compared to basic contracts that provide less coverage.

Figure 15: **Firm price response**
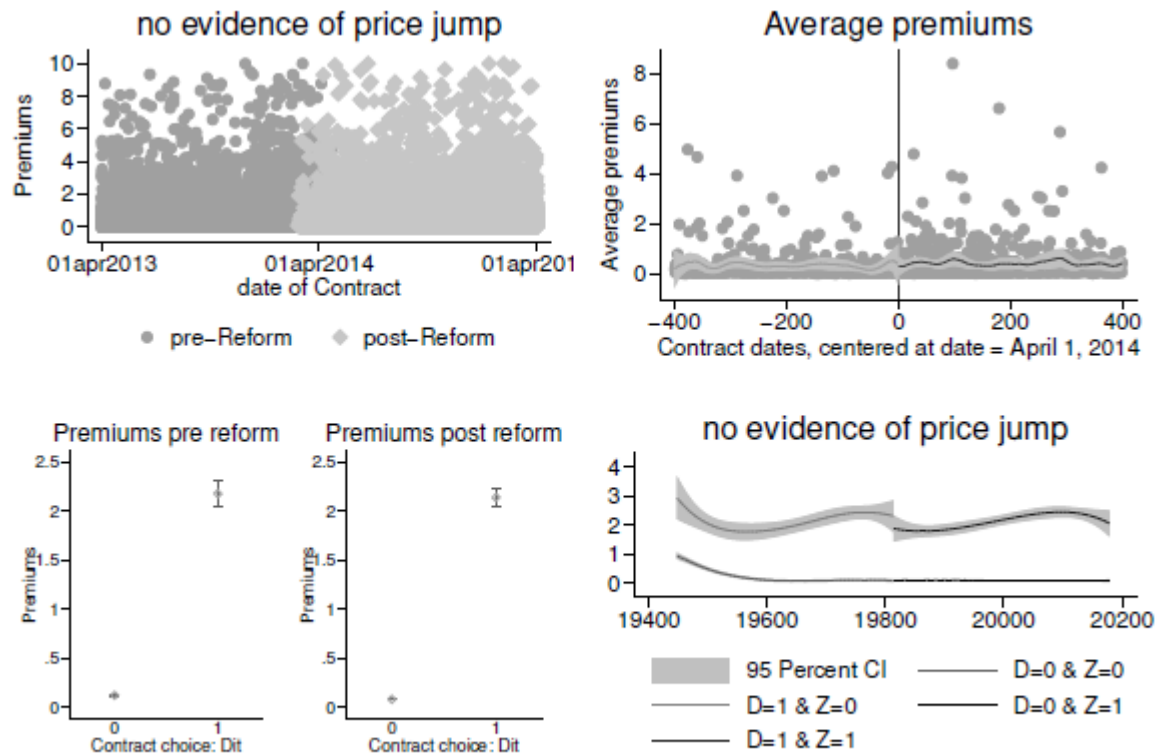
Figures: values are in 1000s of GHC; Limited evidence of significant price Jumps or adjustments

Notes: Figures show the distribution and differential changes in insurance premiums before and after the regulatory reform. The overall distribution is shown in the top panel. In the bottom panel, I show the differential changes across the two different contracts. The 95% confidence intervals are also displayed around the estimates.
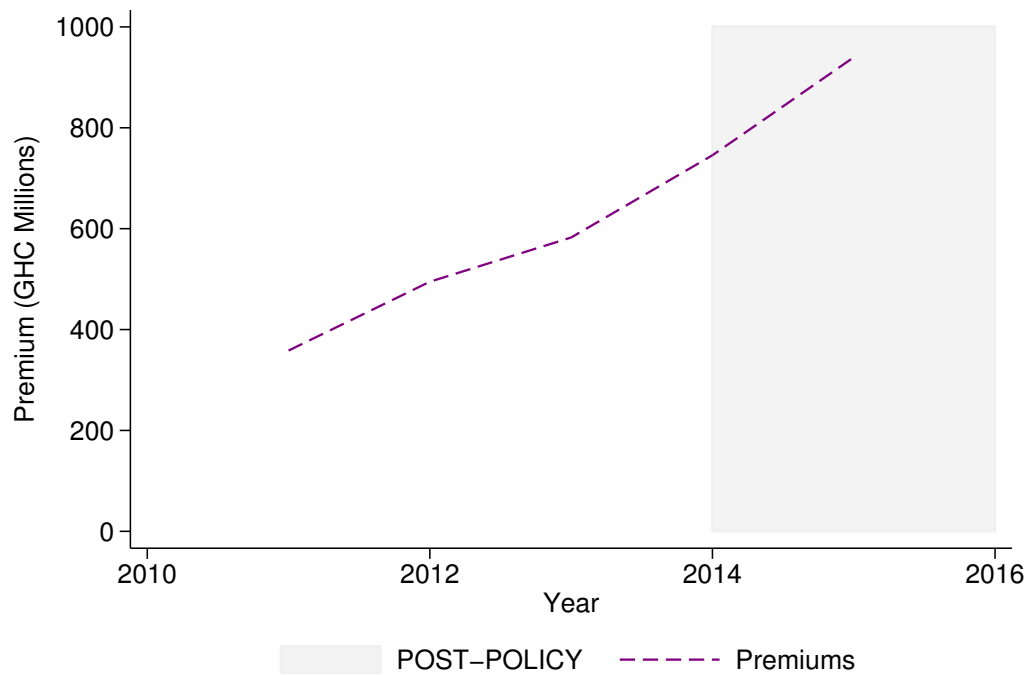
Figure 16: **Effect of reform on insurance pricing**
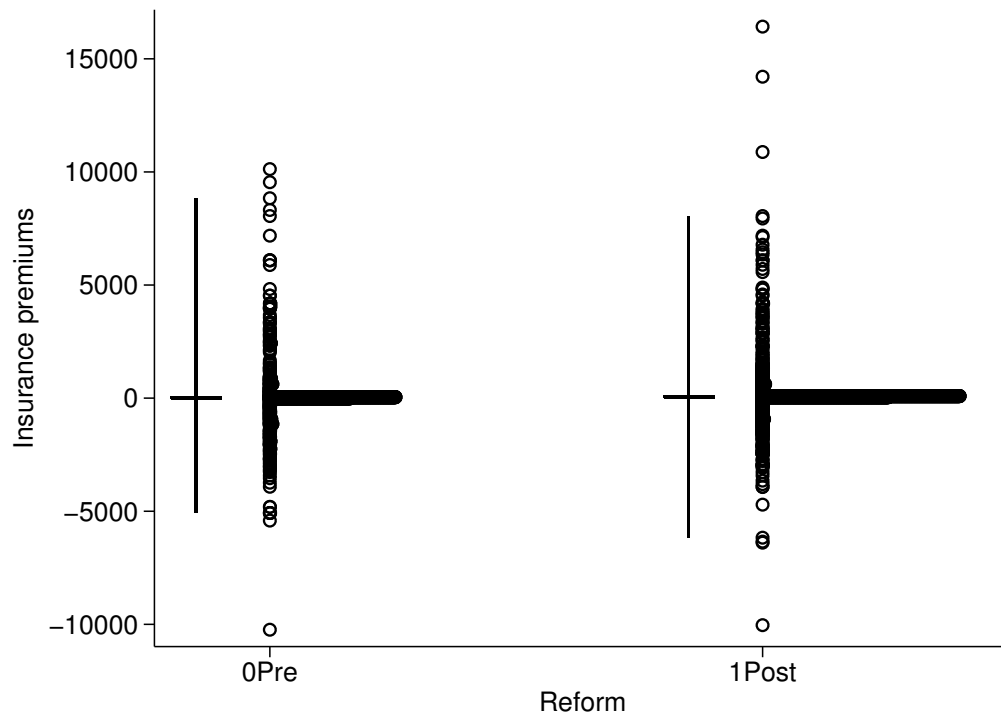
Notes: Figure reflects the raw annual distribution of insurance premiums after customer-level fixed effects are removed from the data. The figure is shown for the period before and after the National policy reform. The sample includes all policy holders. Strip-plots show whiskers containing inner 1.5×inter-quartile range of the observations (Turkey 1977).

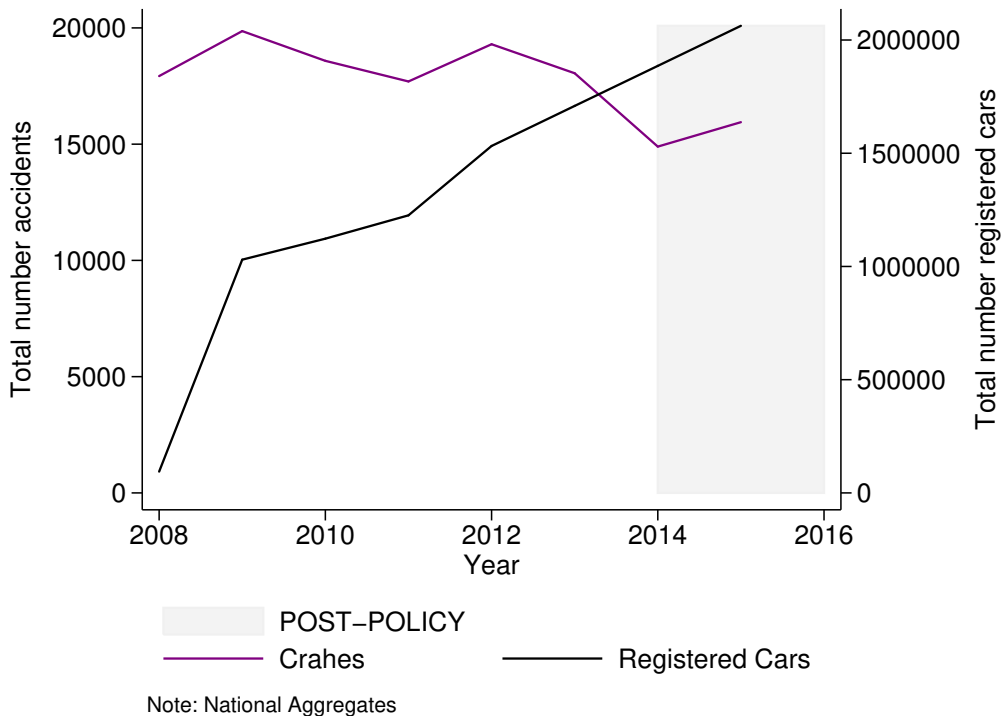Figure 17: **Distribution of market shares and industry growth**
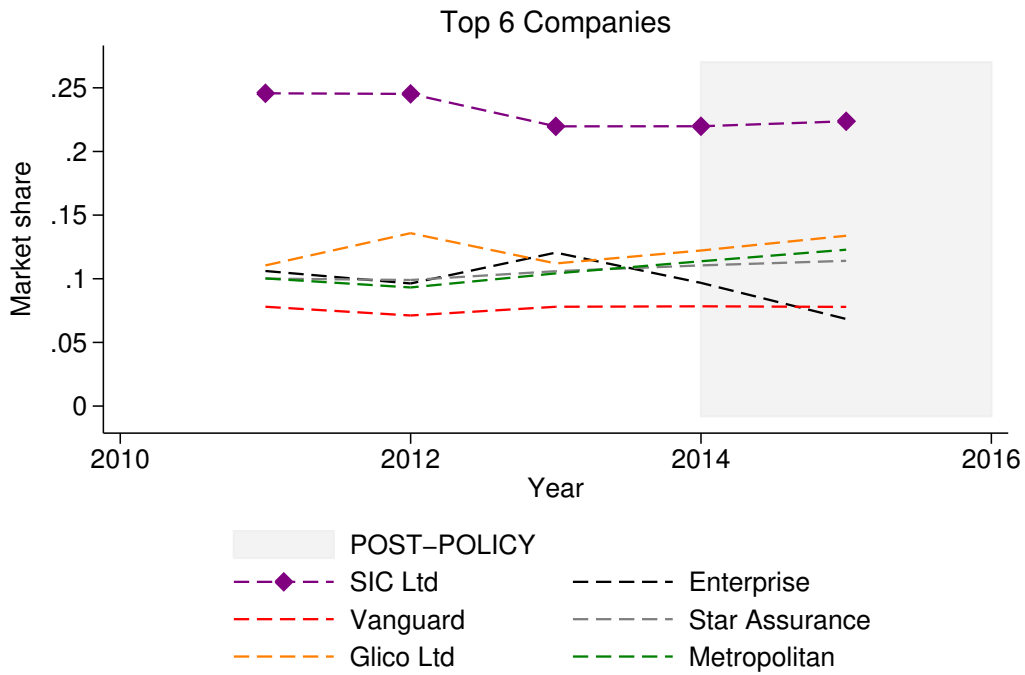
(a) **industry market share**

(b) **industry total premiums**
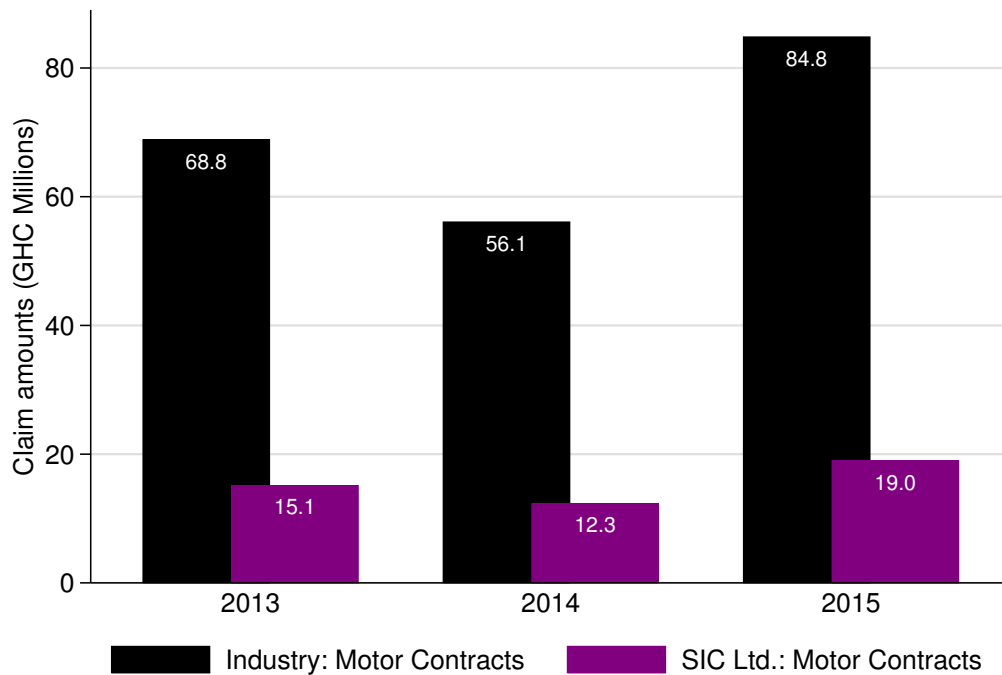
Figure 18: DISTRIBUTION OF AGGREGATE LOSSES AND INDUSTRY CLAIMS

POST–POLICY
Crahes
Registered Cars

Note: National Aggregates

(a) TOTAL CAR ACCIDENTS

Industry: Motor Contracts
SIC Ltd.: Motor Contracts
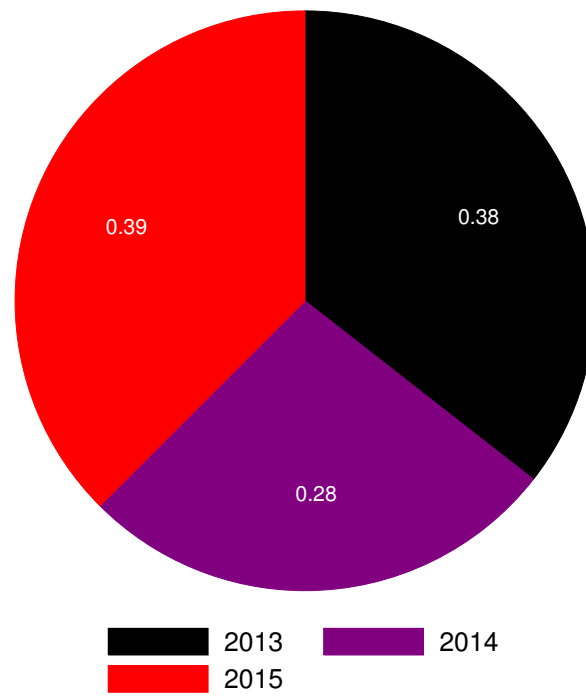
CALCULATIONS: Combine historical reports from NIC & financial statements of insurance companie

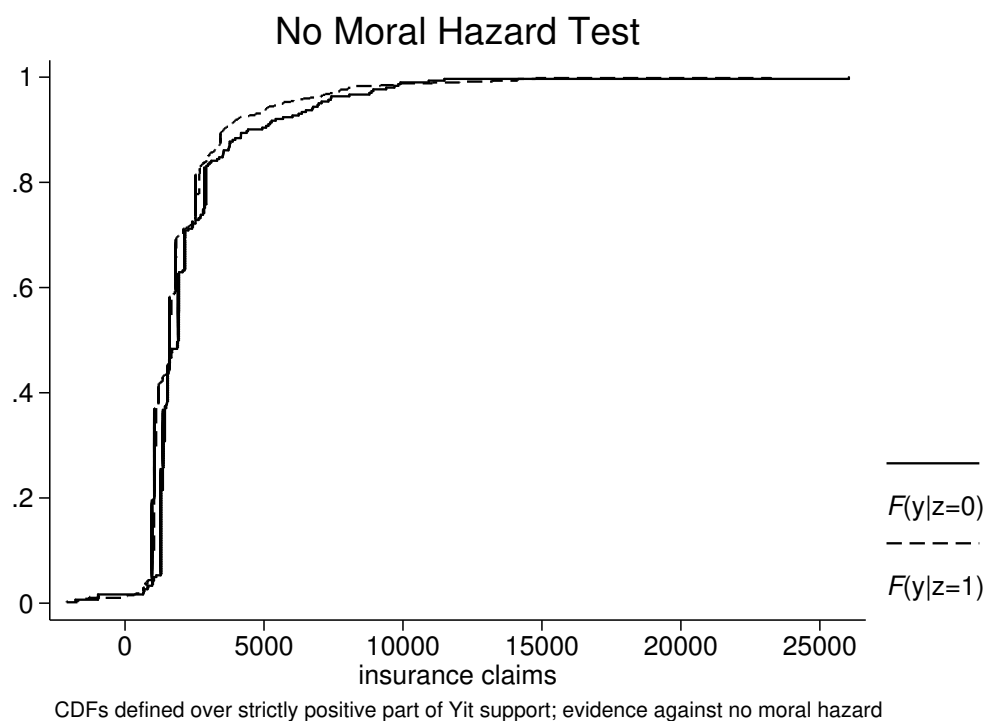(b) INDUSTRY'S TOTAL CLAIMS FOR MOTOR CONTRACTS

Figure 19: **Industry's profits or claims ratio for motor contracts**


CALCULATIONS: Combine historical reports from NIC & financial statements of insurance companies

Figure 20: **SAME POLICY NUMBERS: DISTRIBUTION OF CLAIM AMOUNTS**

No Moral Hazard Test

CDFs defined over strictly positive part of Yit support; evidence against no moral hazard
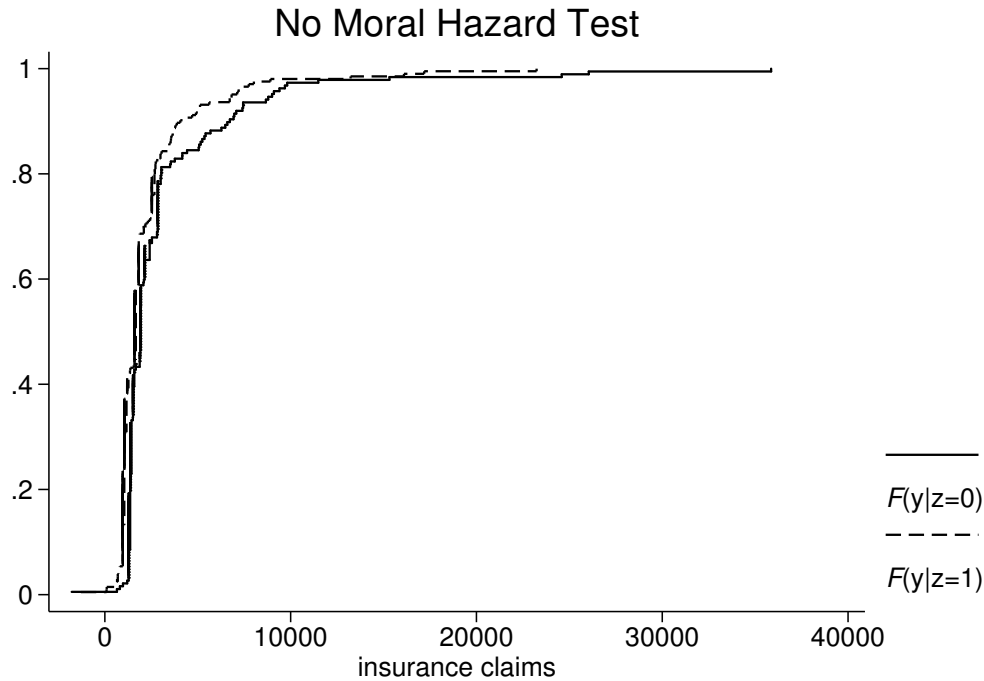
Notes: Figure shows the predicted distribution of claims before and after the no-credit regulation. The distribution in dash corresponds to realizations after the policy $z = 1$. The distributions reflect strictly positive claim amounts. The no-moral hazard test holds for any realization of y.

Figure 21: **Distribution of claim amounts for different time windows**
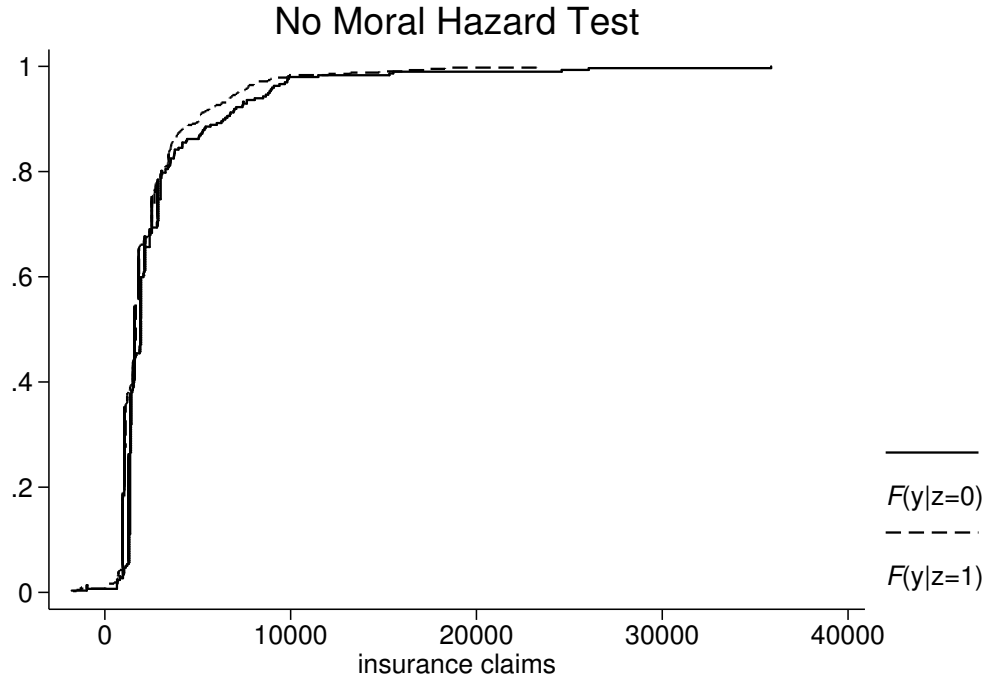
No Moral Hazard Test

insurance claims

CDFs defined over strictly positive part of Yit support; evidence against no moral hazard

$F(y|z=0)$

$F(y|z=1)$

(a) TIME WINDOW 1: 8 MONTHS BEFORE & AFTER REFORM

No Moral Hazard Test

insurance claims

CDFs defined over strictly positive part of Yit support; evidence against no moral hazard

$F(y|z=0)$

$F(y|z=1)$

(b) TIME WINDOW 2: 4 MONTHS BEFORE & AFTER REFORM

Notes: Figure shows the predicted distribution of claims before and after the no-credit regulation across different time windows around the policy. The distribution in dash corresponds to realizations after the policy $z = 1$. The distributions reflect strictly positive claim amounts. The no-moral hazard test holds for any realization of y.

Figure 22: **WINSORIZED DATA: DISTRIBUTION OF CLAIM AMOUNTS**
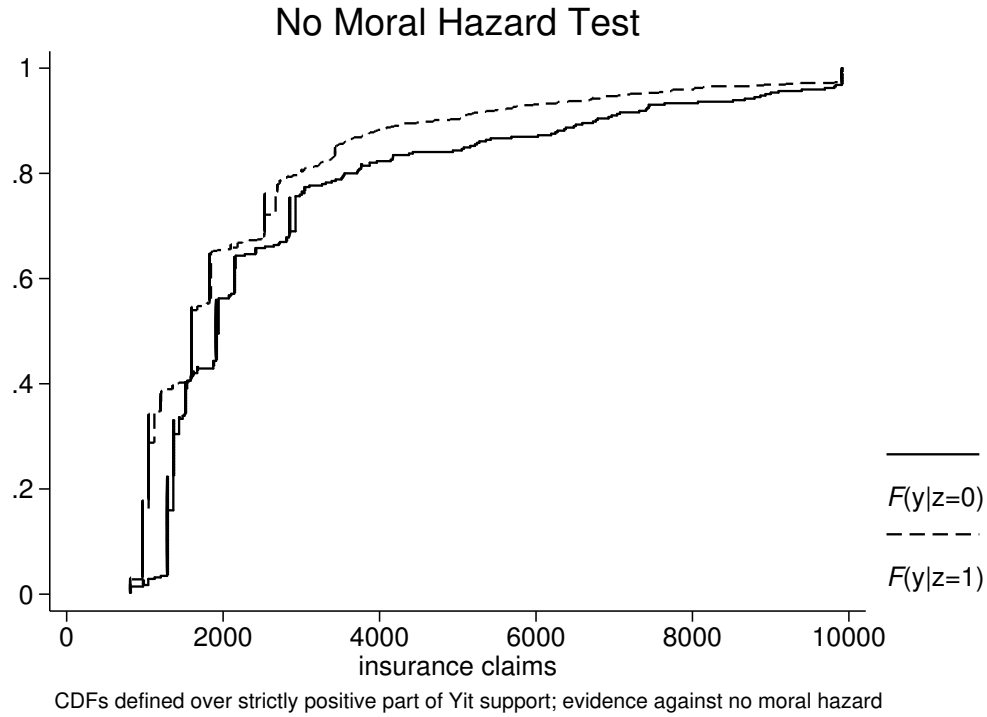
CDFs defined over strictly positive part of Yit support; evidence against no moral hazard

Notes: Figure shows the predicted distribution of claims before and after the no-credit regulation for 95% winsorized data. The distribution in dash corresponds to realizations after the policy $z = 1$. The distributions reflect strictly positive claim amounts. The no-moral hazard test holds for any realization of y.

9 Appendix

A.1 Supplementary results: estimation & zero-interest credit for premiums

A.1.1 Additional results

[Figure 23 about here.]

[Table 14 about here.]

[Figure 24 about here.]

[Figure 25 about here.]

[Figure 26 about here.]

[Table 15 about here.]

[Table 16 about here.]

[Table 17 about here.]

A1.2 Estimation illustration

I directly estimate the bounds: $\hat{\Delta}^l$ and $\hat{\Delta}^u$. For example, $Y = \text{CLAIMS}$

$$\hat{\Delta}^l = 51.95\text{GHC} = \begin{cases} \sup\limits_{z}\{\mathbb{E}[\widehat{DY \mid Z} = z] + \mathbb{E}[\widehat{(1 - D)Y} \mid Z = z]\} & = 118.71 \\ \inf\limits_{z}\{\mathbb{E}[\widehat{DY \mid Z} = z] + \mathbb{E}[\widehat{(1 - D)Y} \mid Z = z]\} & = 66.75 \end{cases}$$

$$\hat{\Delta}^u = 108171.7\text{GHC} = \begin{cases} \inf\limits_{z}\{\mathbb{E}[\widehat{DY \mid Z} = z] + (1 - \widehat{P(z)})G^u\} & = 108224.83 \\ \sup\limits_{z}\{\widehat{P(z)G^l} + \mathbb{E}[\widehat{(1 - D)Y} \mid Z = z]\} & = 52.81 \end{cases}$$

Finally, I bootstrap (nonparametrically) to compute the confidence intervals of $\hat{\Delta}^l$ and $\hat{\Delta}^u$.

A.1.3 Firms: zero-interest credit for premium

I illustrate that a zero-interest rate on insurance premium is a possible outcome in equilibrium, when premiums are regulated. Consider two competing profit maximizing firms (i, j).

Let τ denote the interest rate on the premium's credit. Firms (i, j) are faced with following per-unit demand functions

$$D_i = a - p_i + p_j$$
$$D_j = a - p_j + p_i$$

No price differentiation is allowed. The firms have two price instruments at their disposal: $(p_k; \tau_k)$, $k = i, j$. The loss in revenue for providing insurance on credit is simply $-\tau_k p_k$ and the firms have (independent) constant costs $c(D_i) = c(D_j) = c(D)$.

Program: Since the premium is fixed $p_i = p_j = \boldsymbol{p}$, firms influence premiums by giving away credit as they compete. In particular, the firms choose (τ_i, τ_k) individually and simultaneously (apply Bertrand strategies). Firm i's (similarly j's) objective function is given by

$$\pi_i = (1 + \tau_i)p_i[-(1 + \tau_i)p_i + (1 + \tau_j)p_j)] - \tau_i p_i - c(D)$$
$$\equiv (1 + \tau_i)\boldsymbol{p}[-(1 + \tau_i)\boldsymbol{p} + (1 + \tau_j)\boldsymbol{p})] - \tau_i \boldsymbol{p} - c(D)$$

where the second line uses the fact that the premium is given and fixed. The FOCs (with respect to τ_k) yield the following best-reply functions

$$\tau_k(\tau_{k'}) = \frac{a + (1 + \tau_{k'})\boldsymbol{p} - 2\boldsymbol{p} - 1}{2\boldsymbol{p}}$$

Solving the best-reply functions yields the equilibrium interest rate: $\tau_k^{EQB} = \max(0, \frac{a}{\boldsymbol{p}} - \frac{\boldsymbol{p}+1}{\boldsymbol{p}})$. For certain parameter values of a and $\boldsymbol{p}$ it is possible to have an equilibrium interest rate that is zero (or negative). For instance, such outcome is trivially achieved when $a \in \{0, 1\}$. In addition, when $\boldsymbol{p}$ is really close to a, zero-rate can be achieved. Finally, I note why such a zero-interest rate may coexist with outside credit markets that have higher interest rates: the "credit risk" is much lower in the former. So, higher interest rates from outside channels may reflect their higher default rates, including other reasons (e.g., possibly larger loan sizes, compared to insurance premiums).

A.2 Derivation of proposition 1
I consider the following triangular system

$$Y_i = g(e_i^*(D_i, \alpha_i), \alpha_i^y, \varepsilon_i)$$
$$D_i = \sigma(\alpha_i, Z)$$

This has a direct structural interpretation. $\sigma(.,.)$ the same economic interpretation provided in Section 3.1. In the empirical application the instrument Z should be taken to be policy changes or major events that exogenously induce changes in choice of insurance contracts. The logical indicator D_i equals 1 whenever Y_i is observed; and D_i equals 0 whenever Y_i is not observed, as in the treatment effects or potential outcomes literature. Next, I write the probability of $D_i = 1$ given $Z = z$ as $P(z)$. $P(z)$ is an identified nonparametric index, and captures the insurance probability for individuals with characteristics z. The main object of interest is $\Delta = \mathbb{E}[Y_i(1) - Y_i(0)|Z]$ but this is not identified due to nonrandom selection. The selection problem emanates from the nonrandom assignment of contract choice discussed in the model section. To proceed, I impose the following set of structural restrictions

(**1**) $g(.)$ monotonically decreases in e_i^* for all $(\alpha_i, \varepsilon_i)$

(**2**) Z is independent of $(\alpha_i, \varepsilon_i)$ and Z enters neither $e_i^*(.,.)$ nor $g(.)$

I selectively invoke these restrictions for the identification analysis as needed, in what follows. Restriction **1** is a monotonicity condition, which requires that exerting higher levels of effort will not increase claim outcomes for all consumers i. This is a direct consequence of the Monotone Likelihood Ratio Property MLRP (Holmstrom 1979) in Incentive Theory. The MLRP emerges from the condition required for optimal contract design. In the identification analysis, I employ a slightly weaker version of this which requires it to hold in expectation across only some group of customers; not all i. Next, restriction **2** implies an independence condition $Y_i(d) \perp\!\!\!\perp Z$ for all $d \in \{0,1\}$. Such condition is commonly referred to as an exclusion restriction: no direct causal effect of Z on Y_i.

The approach I adopt requires the timing of the policy to be uncorrelated with selection and that the *average* distribution of contract choice is affected by the instrument (*i.e.*, relevance: a nonzero $\mathbb{E}[D \mid Z = z]$). The bounds approach is particularly useful because it permits multidimensionality of selection in insurance. Note that, the average moral hazard estimate may be relevant in comparing policies that uniformly assign all insureds to either type of insurance policy. Further discussion of the various effects and their relevance are provided in the paper.

Building on the standard "missing outcomes" representation (Manski and Pepper 2000; Lee 2002) I begin by rewriting the implied average structural functions ASF of the mixed model as $\mu_z(1)$:

$$\equiv \mathbb{E}[Y_i(1) \mid Z = z] = \underset{D}{\mathbb{E}}\left[\mathbb{E}[Y_i(1) \mid D, Z = z]\right]$$

$$= Pr(D = 1 \mid Z = z)\mathbb{E}[Y_i(1) \mid D = 1, Z = z] + Pr(D = 0 \mid Z = z)\mathbb{E}[Y_i(1) \mid D = 0, Z = z]$$

$$= P(z)\mathbb{E}[Y_i(1) \mid D_i = 1, Z = z] + (1 - P(z))\underbrace{\mathbb{E}[Y_i(1) \mid D_i = 0, Z = z]}_{\text{not identified}}$$

$$= P(z)\mathbb{E}[g(e_i^*(1, \alpha_i), \alpha_i^y, \varepsilon_i) \mid D_i = 1, Z = z] + (1 - P(z))\mathbb{E}[g(e_i^*(1, \alpha_i), \alpha_i^y, \varepsilon_i) \mid D_i = 0, Z = z]$$

and $\mu_z(0)$:

$$\equiv \mathbb{E}[Y_i(0) \mid Z = z] = P(z)\underbrace{\mathbb{E}[Y_i(0) \mid D_i = 1, Z = z]}_{\text{not identified}} + (1 - P(z))\mathbb{E}[Y_i(0) \mid D_i = 0, Z = z]$$

$$= P(z)\mathbb{E}[g(e_i^*(0, \alpha_i), \alpha_i^y, \varepsilon_i) \mid D_i = 1, Z = z] + (1 - P(z))\mathbb{E}[g(e_i^*(0, \alpha_i), \alpha_i^y, \varepsilon_i) \mid D_i = 0, Z = z]$$

Notice that because $Y_i = Y_i(1)$ whenever $D_i = 1$, I can write

$$\mathbb{E}[Y_i(1) \mid D_i = 1, Z = z] = \frac{\mathbb{E}[D_i Y_i \mid Z = z]}{P(z)}$$

Similarly, because $Y_i = Y_i(0)$ whenever $D_i = 0$, I can write

$$\mathbb{E}[Y_i(0) \mid D = 0, Z = z] = \frac{\mathbb{E}[(1 - D_i)Y_i \mid Z = z]}{(1 - P(z))}$$

Both $\mathbb{E}[D_i Y_i \mid Z = z]$ and $\mathbb{E}[(1 - D_i)Y_i \mid Z = z]$ are immediately identified from the distribution of the observed data $\{(Y_i, D_i, Z)_i : i = 1, ..., I\}$. Particularly, all the terms in $\mu_z(1)$ and $\mu_z(0)$ are identified or known except $\mathbb{E}[Y_i(1) \mid D = 0, Z = z] \equiv \mathbb{E}[g(e_i^*(1, \alpha_i), \alpha_i^y, \varepsilon_i) \mid D = 0, Z = z]$ in $\mu_z(1)$ and $\mathbb{E}[Y_i(0) \mid D = 1, Z = z] \equiv \mathbb{E}[g(e_i^*(0, \alpha_i), \alpha_i^y, \varepsilon_i) \mid D = 1, Z = z]$ in $\mu_z(0)$. Identification therefore hinges crucially on these two unknown terms. These terms are not identified from the distribution of the observed data since one never observes $Y_i(1)$ for consumers with $D_i = 0$ and $Y_i(0)$ for customers with $D_i = 1$ in the data, respectively. The starting point will be Manski's "Worst Case" bounds (Manski 1990). Building on these "Worst Case" bounds, I impose additional restrictions that are governed by agency-theory to provide bounds on the unknown objects of interest.

Worst case bounds of Δ

Suppose that the object $g(.)$ is bounded above and below,

$$G^l \leq g(e_i^*(D_i, \alpha_i), \alpha_i^y, \varepsilon_i) \leq G^u$$

Here G^l and G^u are constant objects and represent the lower and upper bounds on $g(.)$, respectively. In principle, Y_i is bounded within the support $Y_i \in \left[\underline{y}, \ \overline{y}\right]$, and for all customers

i $Y_i(1)$ and $Y_i(0)$ are also bounded within $\left[\underline{y},\ \overline{y}\right]$. The condition on $g(.)$ above is therefore equivalent to setting $G^l \equiv \underline{y}$ and $G'^u \equiv \overline{y}$.

<div align="center">***Worst Case Bounds***</div>

Let the quantity $g(.)$ be bounded as stated above. Section III of Manski 1990, and Proposition 1 of Manski and Pepper 2000 can be used to establish Worst Case bounds on $\triangle$ under the set up as

$$\Delta^l = \sup_z\{\mathbb{E}[D_iY_i \mid Z = z] + (1 - P(z))G^l\} - \inf_z\{P(z)G'^u + \mathbb{E}[(1 - D_i)Y_i \mid Z = z]\}$$

$$\Delta^u = \inf_z\{\mathbb{E}[D_iY_i \mid Z = z] + (1 - P(z))G'^u\} - \sup_z\{P(z)G^l + \mathbb{E}[(1 - D_i)Y_i \mid Z = z]\}$$

where Δ^l and Δ^u denote lower and upper bounds on $\triangle$, respectively. These are the worst case best possible bounds, and without further information the bounds are sharp. In general, this set $\Delta \in [\Delta^l, \Delta^u]$ may be wide and thus not very informative. It is useful to note that these "Worst Case" bounds in themselves do not directly help for the purposes of identifying moral hazard. I impose additional plausible restrictions that are inspired by economic theory to tighten the bounds in the next series of identification analysis. Suppose, for a moment, that one ignores the gains from the intersection of the bounds across all z. Then the implied width of the ATE bounds above is

$$\Delta^u - \Delta^l = G'^u - G^l$$

This is derived from substituting for the various objects, and then canceling out identical terms. To further illustrate that the above set is less informative in the asymmetric information context, consider the canonical binary choice model where $Y_i \in \{0, 1\}$. In the empirical analysis, one of the outcome of interest is binary: that is, whether or not an accident (or or loss) occurred. Here, it follows immediately that $G^l = 0$ and $G'^u = 1$. Therefore the corresponding lower and upper bounds for the average effect $\triangle$ are $\Delta^l = \mathbb{E}[D_iY_i \mid Z = z] - (P(z) + \mathbb{E}[(1 - D_i)Y_i \mid Z = z])$ and $\Delta^u = \mathbb{E}[D_iY_i \mid Z = z] + (1 - P(z)) - \mathbb{E}[(1 - D_i)Y_i \mid Z = z]$, respectively. The width of these bounds simplifies to $\Delta^u - \Delta^l = 1$. Here $P(z)$ is simply the insurance choice probability for individuals with characteristics z.

Tightening the bounds of $\triangle$

I investigate the identifying power of certain plausible restrictions. The restriction I impose is governed by the theoretical considerations of agency models and the empirical application process considered in this paper.

Customers' Effort Supply

In a standard mixed adverse selection and moral hazard model of insurance, customers who choose higher coverage contracts are more likely to exert lower levels of effort. As in agency theory, this may in part stem from information and preference asymmetries. Typically, the principal can observe the outcome; but not the action of the customer. Notwithstanding, the actions and/or efforts of the customer can be monitored in theory; but in practice obtaining complete information could be prohibitively expensive: "costly verification" (Townsend 1979)[47]. Next, customer's preferences (e.g. risk aversion) may differ from that of the insurer, and so to the extent that the actions of the customer that may be considered beneficial to the insurer could be costly to the customer, it is likely the consumer may under supply his level of effort: "un-aligned preferences". To this end, I formally impose the inequality restriction that for each customer i

$$e_i^*(1, \alpha_i) \leq e_i^*(0, \alpha_i)$$

This implies that customers that select higher coverage contracts or buy insurance will not increase their supply of effort e.g, via seat-belting or any implied precautionary action in the automobile insurance context. Combining this with structural restriction **2**, I have that for all customers i

$$Y_i(1) \geq Y_i(0)$$
$$g(e_i^*(1, \alpha_i), \alpha_i^y, \varepsilon_i) \geq g(e_i^*(0, \alpha_i), \alpha_i^y, \varepsilon_i)$$

Notice that the agency-theory restriction consequently yields a version of the usual monotone treatment response MTR condition (Manski 1997). That is, choosing a higher coverage contract will not increase customer's outcome. It is also straightforward to see that the above condition will restrict the sign of the average effect. In the identification analysis, however, I use a much weaker version of the condition

$$\mathbb{E}[Y_i(1) \mid D_i = d, Z = z] \geq \mathbb{E}[Y_i(0) \mid D_i = d, Z = z]$$

for all $z \in \mathbb{Z}$ and $d \in \{0, 1\}$. To illustrate, let $d = 0$, then this condition says $\mathbb{E}[Y_i(1) \mid D_i = 0, Z = z] \geq \mathbb{E}[Y_i(0) \mid D_i = 0, Z = z]$. Similarly for $d = 1$, $\mathbb{E}[Y_i(1) \mid D_i = 1, Z = z] \geq$

---

[47]In this case, the principal may wish to charge more premium to embark on more verification. This, however, is unlikely to hold. For example, in the empirical setting, insurers have little or no room to adjust insurance prices. The market including premium setting is highly regulated and controlled by the government, where insurance companies are required to follow a proposed premium formula in selling contracts. The empirics provide suggestive evidence of price rigidity: firms did not quickly adjust prices following the introduction of reform.

$\mathbb{E}[Y_i(0) \mid D_i = 1, Z = z]$. The use of this condition is motivated by the following. First, the original restriction is stronger because it must hold for all the customers i. The latter only need it to hold in expectation across some group of consumers. Identified bounds on the objects of interest using the weaker restriction actually coincides with that of the stronger MTR restriction. This can be viewed as an improvement given that weaker restrictions are generally preferred, and easier to rationalize in practice. Next, because I am interested in identifying the average moral hazard, the weaker condition is sufficient. Under this weaker condition, the bounds on the unknown objects are

$$\mathbb{E}[Y_i(1) \mid D_i = 0, Z = z] \in \left[\frac{\mathbb{E}[(1 - D_i)Y_i \mid Z = z]}{(1 - P(z))}, \ G^u \right]$$

$$\mathbb{E}[Y_i(0) \mid D_i = 1, Z = z] \in \left[G^l, \frac{\mathbb{E}[D_iY_i \mid Z = z]}{P(z)} \right]$$

for all $z \in \mathbb{Z}$. Note that the identified bounds for the unknowns above must hold for all $z \in \mathbb{Z}$. This can be viewed as a consequence of restrictions **2**. I can therefore intersect the bounds across all the possible values that z can take. The implied bounds on the quantities $(\mu_z(1), \mu_z(0))$ become

$$\sup_z \{\mathbb{E}[D_iY_i \mid Z = z] + \mathbb{E}[(1 - D_i)Y_i \mid Z = z]\} \ \leq \mu_z(1) \ \leq \inf_z \{\mathbb{E}[D_iY_i \mid Z = z] + (1 - P(z))G^u\}$$

$$\sup_z \{P(z)G^l + \mathbb{E}[(1 - D_i)Y_i \mid Z = z]\} \ \leq \mu_z(0) \ \leq \inf_z \{\mathbb{E}[D_iY_i \mid Z = z] + \mathbb{E}[(1 - D_i)Y_i \mid Z = z]\}$$

Next, the resulting best possible bounds on the average treatment effect Δ: the main object of interest are

$$\Delta^l = \sup_z \{\mathbb{E}[D_iY_i \mid Z = z] + \mathbb{E}[(1 - D_i)Y_i \mid Z = z]\} - \inf_z \{\mathbb{E}[D_iY_i \mid Z = z] + \mathbb{E}[(1 - D_i)Y_i \mid Z = z]\}$$

$$= \sup_z \{\mathbb{E}[Y_i \mid Z = z]\} - \inf_z \{\mathbb{E}[Y_i \mid Z = z]\}$$

$$\Delta^u = \inf_z \{\mathbb{E}[D_iY_i \mid Z = z] + (1 - P(z))G^u\} - \sup_z \{P(z)G^l + \mathbb{E}[(1 - D_i)Y_i \mid Z = z]\}$$

QED

This uses the assumption that $Y_i(1)$, and $Y_i(0)$ are (conditionally) independent of Z. First, observe that the lower bound Δ^l simplifies to a simple difference estimator. The width $\Delta \in [\Delta^l, \Delta^u]$ is analogously defined, and the expressions further simply under the binary choice model where $G^l = 0$ and $G^u = 1$. Without intersecting the bounds across all z, the ATE lower bound becomes $\Delta^l = 0$. In the empirical analysis, I intersect the resulting bounds across z using the sup and inf operators, which provide informative estimates for Δ^l that are non-zero. Since the inequality restriction provides improvements to the lower bound, Δ^l will be the main focus for the analysis of moral hazard effects.

A.3 Additional Discussions

A.3.1 Why were companies willing to accept credit payments before the reform?

(1) Premium targets Each local insurance office is given a premium target per contract period, so there were clear incentives to push credit to customers. These target levels trickle down to the individual staff.[48]

(2) Existence of intermediaries: insurance agents and brokers. Commission-motivated agents developed personal relationships with their clients and provided insurance on credit. This was not considered a challenge to the companies since the intermediaries have a better incentive to collect premium debts: most insurance companies would not pay full commissions due the agents and brokers until the premiums are paid.

(3) Client-centric and the norm of keeping business In the past, government organizations were are among the top insurance clients. However, funding from the government is usually delayed and so due to their size in the customer space, the provision of insurance on credit to such institutions was deemed a way of keeping the business of insurance firms. The insurance companies assumed that government debts will eventually be paid no matter how long it takes, further promoting the sale of contracts on credit with recent extensions to individual customers.

A.3.2 Recovering claims for basic-liability contracts

From the insurer's data, I cannot directly use the observed claim outcomes under $D_{it} = 0$, basic contracts. That is, the data at hand do not allow for direct comparison of the outcomes under treatment status $D_{it} = 1$ versus $D_{it} = 0$, particularly for claims. The reason is that the insurer's claim dataset, while it reflects liabilities to both own and other parties damages under the comprehensive insurance, it excludes the liability to own damages under the basic insurance. Estimates will clearly be biased upward if this is ignored. I approach this in two ways:

First, I follow an indirect approach due to Chiappori et al. (2006) to circumvent this challenge. To illustrate, denote by $\bar{Y}_{it0}$ the observed claims in the insurer's dataset (which excludes the liabilities to customer i's own damages) and Y_{it0} the true counterfactual claims under $D_{it} = 0$. The solution is to assume that the distribution of Y_{it0} conditional on $\bar{Y}_{it0}$

---

[48]There is anecdotal evidence that the staff use their family and friends for that purpose. Company workers served as guarantees to spread insurance premiums for their families and friends, since members could not afford to pay all at once, especially for the comprehensive cover. Such phenomenon grew overtime: the sale of insurance on credit was largely overlooked in the companies, even at the top level with no sanctions against the staff who do same.

depends only on customer i's observed vector of characteristics, X_{it}. Under this assumption, one can use the observed claims distribution on $D_{it} = 1$, comprehensive contracts for observationally similar customers to recover that of Y_{it0}.[49] In practice, I construct an customer level index or score based on the observed characteristics and outcomes. Next, I define the notion of "similarity" to be customers that have the closest scores. These are then matched accordingly. This approach is stringent as exemplified by: for $D_{it} = 0$ (i) average claim amount is GHC55.8 compared to a raw amount of about zero; (ii) average loss occurrence is 0.037 compared to about a zero rate initially. Note that the claim and loss occurrence information for contract $D_{it} = 1$ remain unchanged. All analysis use these outcomes.

Second, as a robustness check, I analyze moral hazard for claim events that are only covered under both contracts (ignores the above imputation). These are third-party events that both comprehensive and basic-liability contracts cover and are directly available.

A.4 Future work: preliminary results

A.4.2 Co-environmental benefits: did the policy led to lower vehicle emissions, PM 2.5?

Data: I draw on high resolution satellite database from National Aeronautics and Space Administration (NASA)–MERRA-v2. This is a global reanalysis database that assimilates space-based observations of aerosols and represent their interactions with other physical processes in the climate system. MERRA-v2 begins in 1980 with spatial resolution of 50km in latitude direction. Particulate Matter PM 2.5 (kg/m^3), wind (m/s), temperature, and humidity for the entire country were extracted, and then aggregated to the district level i. I link discontinuity in PM 2.5 to the policy as follows:

$$\text{PM2.5}_{it} = \gamma_0 + \gamma_1 \text{Policy}_t + \gamma_2 \mathbf{X}_{it} + \epsilon_{it}$$

Where $\text{Policy}_t = \mathbf{1}[\text{Date} > \text{April 2014}]$; $\mathbf{X}_{it}$ includes three weather control variables in month t (wind speed, temperature and humidity), month of year (MOY) dummies, and district-level dummies. The results are shown in Figure A5.

[Figure 27 about here.]

A.4.1 Selection: do the switchers signal as bad risk-types?

---

[49]An important feature about this approach is that it is more stringent and thus should go against the moral hazard results. The imputation is done for $D_{it} = 0$ by borrowing information from the distribution of $D_{it} = 1$ claims. Chiappori et al. (2006) provides additional details.

From the perspective of insurance firms, the switchers (consumers who bought insurance on credit) could be identical to the non-switchers based on the observable characteristics of consumers. Does this hold for unobservables? In contrast, results in Table A5 and Figure A6 indicate that the switchers signal as bad risk-types: residual claims (unobserved) are systematically worse for the switchers, compared to the other various categories of consumers.

[Table 18 about here.]

[Figure 28 about here.]

Table A1: **Heterogeneity in Moral Hazard (MHE)**

Certificate Type	LOSS –Bounds–	95% CI		Discount Quartile	LOSS –Bounds–	95% CI
Private	lb 0.007	[0.0001,0.01]		q_1	lb 0.01	[0.0025,0.0271]
Commercial	lb 0.17	[0.007,0.27]		q_2	lb 0.005	[0.0001,0.0078]
				q_3	lb 0.0025	[0.0025,0.0151]
				q_4	lb 0.004	[0.0028,0.0225]

Notes: Table shows the lower bound on moral effects across customer business class (private versus commercial) and quartiles for premium discounts. CI denotes confidence interval. lb denotes lower bound on moral hazard. q_1, q_2, q_3 and q_4 correspond to the first, second, third and fourth quartiles of premium discounts respectively. The 95% confidence intervals are based on 999 nonparametric bootstrap resamples for the various objects of interest.

Table A2: **Data Summaries**

Selected Variables	Mean	Min	Max
Claim amount (GHC)	99.54	0	135,588.9
$\mathbf{1}[Loss = Yes]$	0.04	0	1
$\mathbf{1}[Credit = Yes]$	0.27	0	1
Year of manufacture	2001.15	1957	2015
Cubic capacity (cm^3)	2477.973	1.4	119467.0
Seat capacity	5.228222	1	56
NCD level	4.068628	0	11
Loading	76.97456	-44.26	13,803.26
Premium (GHC)	440.2559	0.01	69,029.25
Contract dates	—	01apr2013	31mar2015

Notes: 27% of customers purchased insurance on credit prior to 2014 policy reform. The number of policies (observations) are the end of the sample period is 31,877.

Table A3: **Summaries−1**

Pre-reform	Mean	Min	Max
Claim amount (GHC)	112.87	0	47,385.1
$\mathbf{1}[Loss=Yes]$	0.041	0	1
$\mathbf{1}[Credit=Yes]$	0.27	0	1
Year of manufacture	2001.26	1957	2014
Cubic capacity (cm^3)	2519.36	1.6	99,999.0
Seat capacity	5.23	1	56
NCD level	4.32	0	11
Loading	93.86	0	13,803.26
Premium (GHC)	538.36	0.01	69,029.25
Contract dates	—	01apr2013	01apr2014

Table A4: **Summaries–2**

Post-reform	Mean	Min	Max
Claim amount (GHC)	92.41	0	135,588.9
$1[Loss = Yes]$	0.038	0	1
$1[Credit = Yes]$	—	—	—
Year of manufacture	2001.09	1957	2015
Cubic capacity (cm^3)	2455.85	1.4	119,467.0
Seat capacity	5.22	1	56
NCD level	3.93	0	11
Loading	67.94	-44.26	5,851.54
Premium (GHC)	387.77	0.17	23,519.06
Contract dates	—	01apr2014	31mar2015

Table A5: **CONDITIONAL DISTRIBUTION OF RESIDUAL CLAIMS**

Consumer Type	Mean	25th PCT	50th PCT	75th PCT	Skewness	Regime
Always Comprehensive	-141.18	-344.95	-232.56	-70.27	20.21	PRE-POLICY
Switchers (Credit-customers)	-56.91	-429.38	-318.85	-175.07	28.96	
Always Basic-liability	-1.98	-89.45	-59.78	-34.11	21.56	POST-POLICY
Switchers (Credit-customers)	128.89	-188.32	-59.06	-18.57	28.91	

Notes: Table shows the distribution of residual claims (unobserved) for two regimes. In the top panel, the distribution of customers who always buy comprehensive contracts is compared with that of those who bought insurance on credit, pre-policy. In the bottom panel, the distribution of customers who always buy basic-liability contracts is compared with those who bought insurance on credit, post-policy. There is evidence of worse claim outcomes for switchers (much right-skewed) in all cases. Together, this evidence suggestive that the switchers are generally bad risk-types. Bundling credit with insurance appears to attract bad risk customers.

Figure A1: **The Model's Timing**

Timing: Sequential moves, diagrammatically

Stage 1 — Observe Type: α_i

Stage 2 — Contract choice: $d=0$ vs $d=1$

D_i

Stage 3 — Exert costly effort: e_i

Outcomes realized
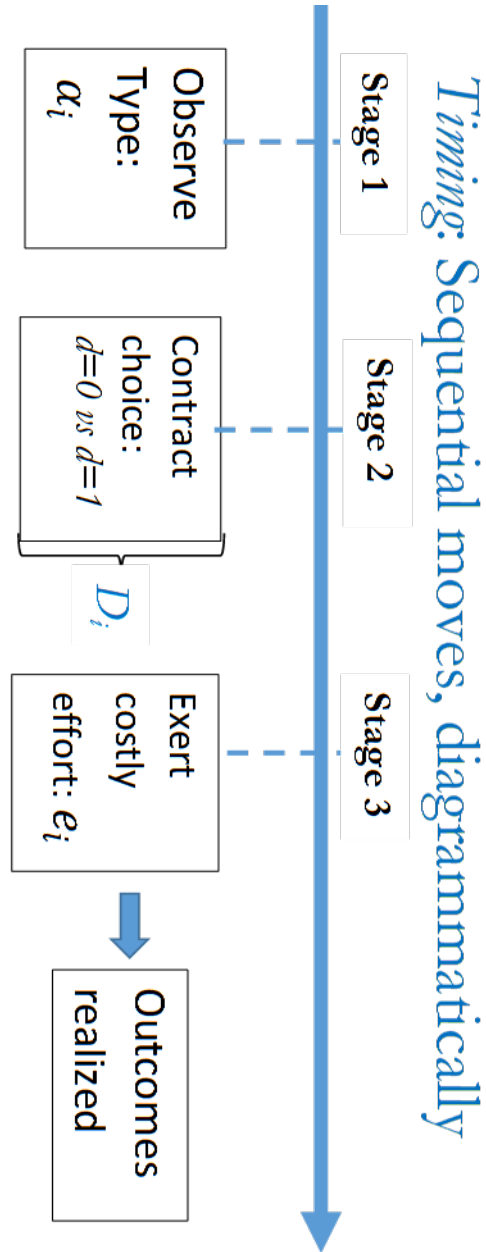
Notes: Figure shows the timing of the mixed-economic model; illustrating the interplay between multi-dimensional selection and moral hazard. Contract choice depends on selection. In turn, the optimal choice of effort depends on contract choice and selection attributes.

Figure A2: L_2-**Type — Moral Hazard Test**

Distribution of Test Statistic, T

The distribution of test statistic is based on 999 nonparametric bootstrap resamples
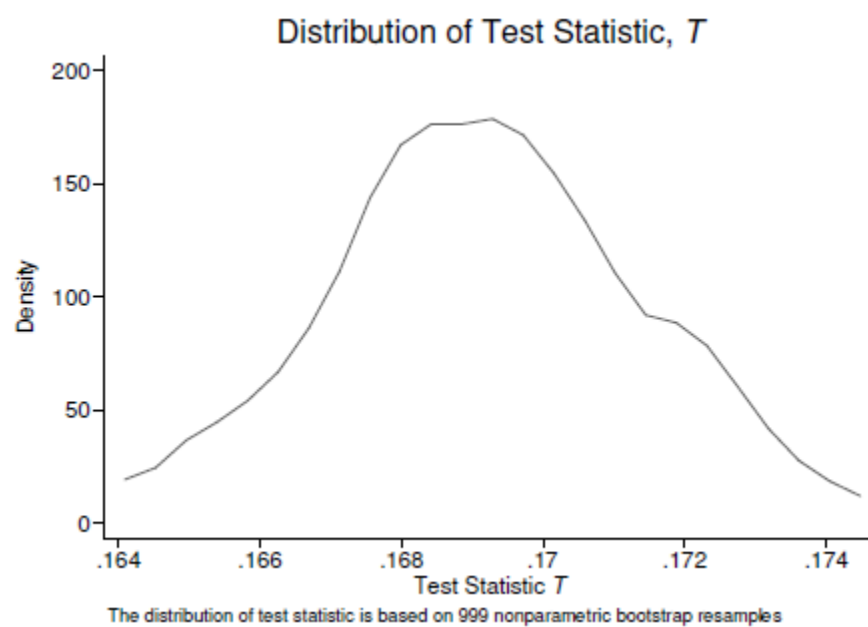
Figure A3: **Gasoline Prices in Ghana**

| Distributional moments: gas prices		
	Mean (US$/$L$)	SD
Pre-reform	1.06	1.04
Post-reform	1.02	1.03

Notes: Figure shows the gasoline prices in Ghana over the relevant period: March 2013 to March 2015. The figure is due Trading Economics (http://www.tradingeconomics.com/ghana/gasoline-prices); which is in turn based on data reported by the National Petroleum Authority NPA. As shown, the average and standard deviation of gasoline prices before the April 2014 reform is 1.06 US$/L and 1.04 respectively; average and standard deviation of prices after the reform are 1.02 US$/L and 1.03, similarly. While there are a few observable fluctuations in gasoline pump prices across various months, the distribution of prices before and after the April 2014 remained fairly stable, as depicted by the distributional moments. Existing national support programs intended to safeguard consumers and the public against general price shocks may explain the stability in price distributions.

Figure A4: **Timelines of Policy**

OCT 12, 2013
POLICY AGREED

APR 1, 2014
POLICY IMPLEMENTED
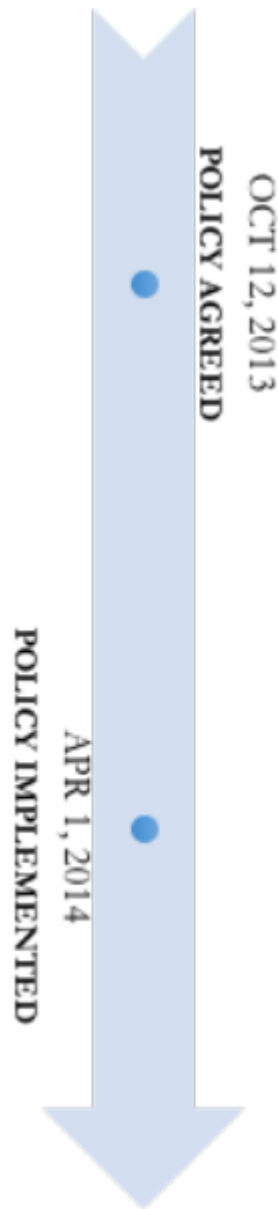
Notes: Figure displays the timelines regarding the policy reform. The NIC agreed on the policy on October 12, 2013. The implementation/announcement of regulation took place on April 1, 2014; suggesting an implementation lag of about 7 months.

Figure A5: DISCONTINUITY IN PM 2.5 AT POLICY CUT-OFF

(a) RESULTS FOR LOCAL LINEAR REGRESSION

(b) RESULTS FOR QUADRATIC REGRESSION
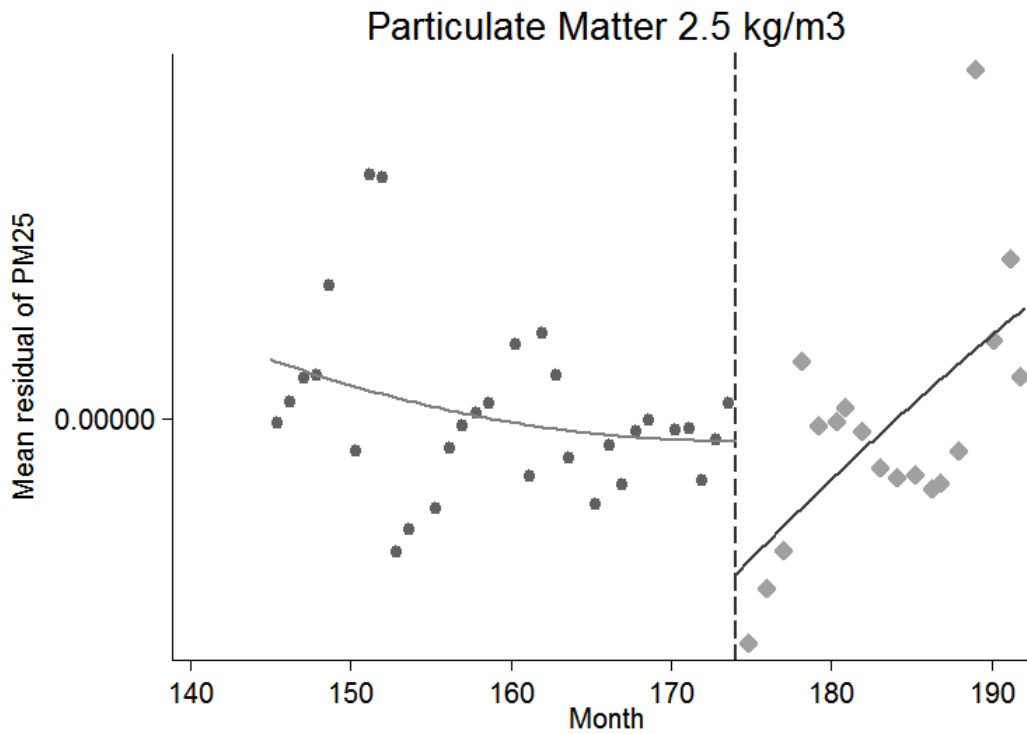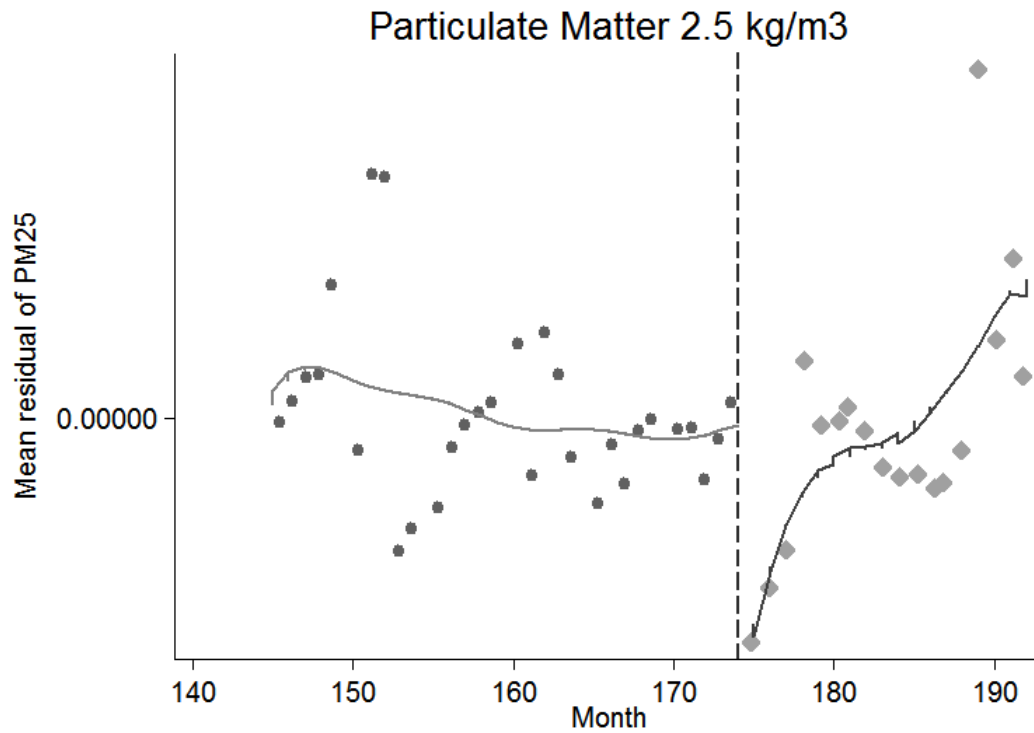
Notes: Figure (a) displays mean residual PM2.5 on each side of the policy-cutoff by month and **local linear regressions** on each side of the cutoff; (b) replicates (a) but for **quadratic regressions** on each side of the cutoff. In both cases, there is suggestive evidence of immediate reduction in PM 2.5. Estimates range between [-1.0 EXP-8; -5.7 EXP-9]**.

Figure A6: **Stripplot showing distribution of residual claims**
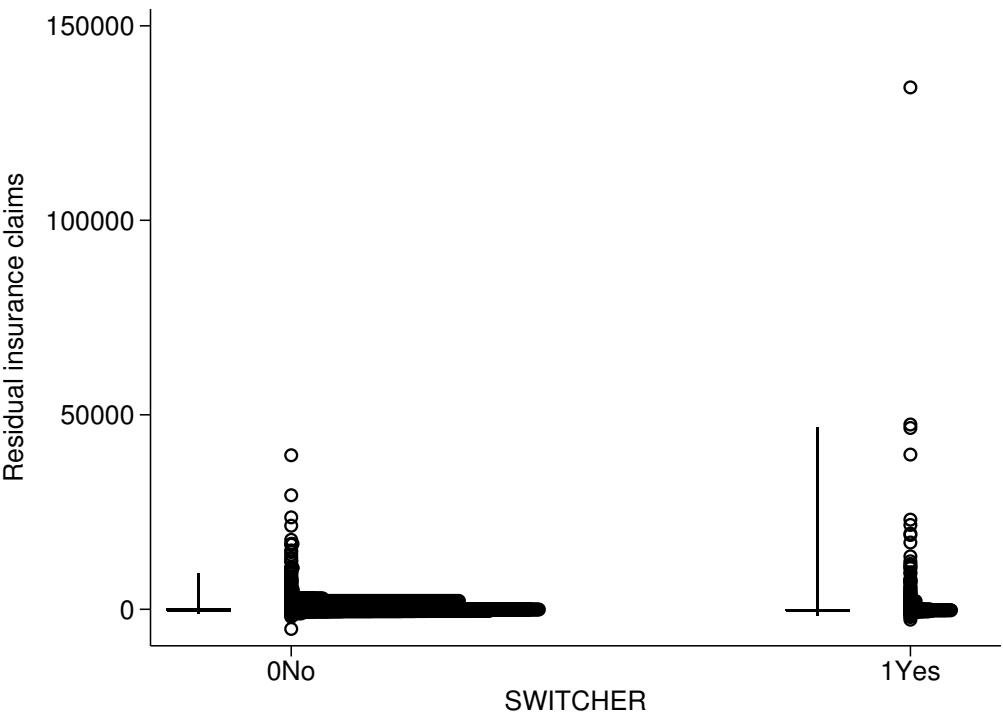
(a) **always comprehensive customers vs. switchers**
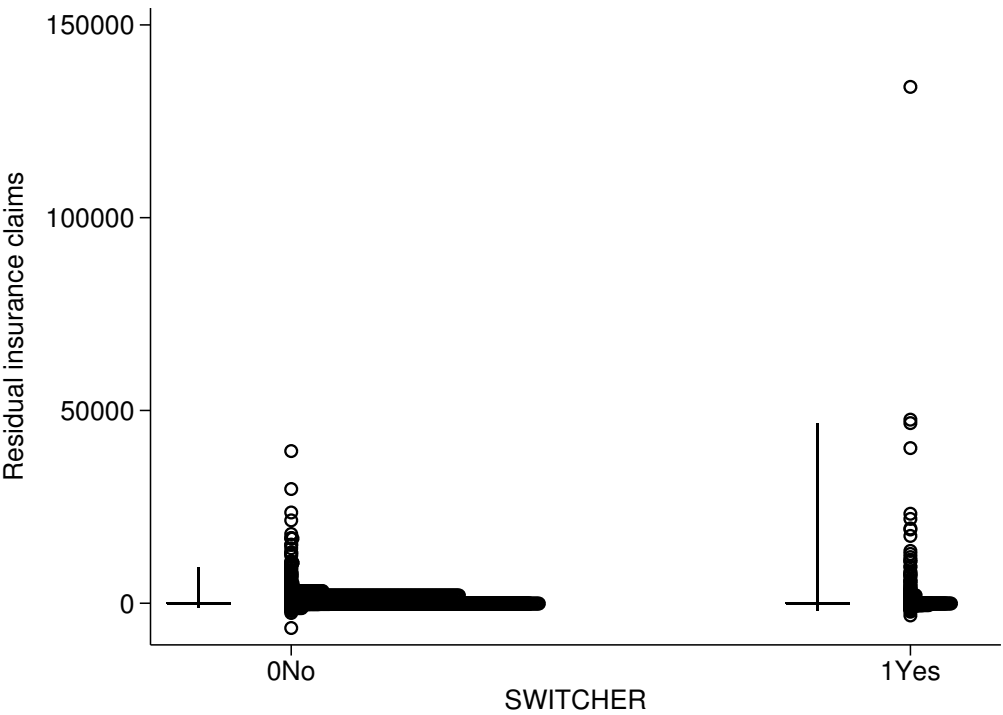
(b) **always basic-liability customers vs. switchers**